WILDFIRE IN THE WEST: AN INITIAL ANALYSIS OF WILDFIRE IMPACTS ON HYDROLOGY AND RIVERBED GRAIN SIZE IN RELATION TO SALMONID HABITAT

by

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ABSTRACT

Wildfire in the West: initial analysis of wildfire impacts on hydrology and riverbed gain size in relation to salmonid habitat

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The wildfire season is increasing due to warmer temperatures, increasing aridity, and changes in forest management. These climate-driven changes to wildfire regimes have both beneficial and detrimental impacts on biological communities and physical processes. More research is needed to better understand how people, landscapes, and aquatic communities are affected within and downstream from wildfires. Here, I study economic effects and human perceptions of wildfire trends in the western US, changes in the magnitude of flooding following wildfires, and changes in salmonid habitat downstream of fires. I answer three overarching questions: 1) How do changing fire characteristics influence adaptive management in the Intermountain West?, 2) How well can we predict the magnitude of change in rainfall-runoff ratios in wildfire-affected areas using readily available environmental metrics such as watershed area, burned area and burn severity?, 3) How does overall grain size distribution change within the stream network and what are the subsequent effects on egg incubation, fry emergency, and female salmonid's ability to dig redds?

Chapter 2 demonstrates increases in wildfire frequency and area burned within the Intermountain West and the heterogeneous positive and negative economic impacts across five economic sectors on communities affected by fire. We also conclude that most managers and policy decision-makers are aware of changes in fire trends, but human-factors, such as bureaucracy and budget constraints, hinder them from changing management practices. Chapter 3 demonstrates that wildfires increase the magnitude of rainfall-runoff ratios and that increases can be singular flood events or persistent increases. Chapter 4 examines the change of riverbed grain sizes within two rivers affected by fire and the subsequent effects on salmonid habitat in relation to egg incubation, fry emergence, and female's ability to dig redds. I show that previous metrics used to classify habitat quality are inconsistent with one another, even when the same habitat characteristic is being measured. I also show that, immediately after a fire, there is a significant fining effect and that habitat tends to remain unchanged or decrease in habitat quality. The combined results show that wildfires have significant impacts on biological communities and physical processes. More work is needed to better understand how different variables influence the magnitude of impacts from wildfires and why different areas respond differently to wildfires.

(167 pages)

PUBLIC ABSTRACT

Wildfire in the West: initial analysis of wildfire impacts on hydrology and riverbed gain size in relation to salmonid habitat

Natalie Gillard

Historically wildfires have been beneficial to forests, however, human developments have encroached on forests when wildfire was artificially suppressed by federal and state agencies. The area burned by wildfire each year has increased twenty-fold in the past three decades. Large, high severity fires pose increased threats to human and aquatic communities within and downstream of the burned area due to post-wildfire effects on flooding and sedimentation. We need to understand the impacts of wildfires to be able to mitigate their damages and to recognize their potential benefits. This research addresses the questions: 1) Do wildfires impact rural and urban economies differently and what are managers doing to adapt management strategies? 2) Do floods increase after wildfire, and if so, by how much? 3) Do wildfires affect fish habitat, and if so, how?

Chapter 2 provides insight into both positive and negative economic impacts on rural and urban economies after a wildfire, and brings to light manager's inability to change their management strategies due to constraints such as budget limitations. Chapter 3 measures how floods change in nine basins after a wildfire occurred, and reveals that floods may increase up to 880 percent after a fire. Chapter 4 demonstrates that fish habitat is significantly altered after wildfires and why change is harmful to the fish. This work shows that wildfire significantly changes the burned and surrounding area, and that more work is needed for a better understanding of how to predict how a specific area will respond to wildfire.

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CHAPTER 1

INTRODUCTION

Climate change is altering wildfire regimes across the western US, affecting both human and aquatic communities. Historically, wildfires played an essential role in ecosystem health, by removing underbrush, stopping the spread of disease and invasive species, stimulating new growth and improving habitat for native species (Cal Fire, n.d.). However, as the climate changes, fire regimes are shifting, and increasing aridity has already led to an earlier onset of spring and longer summers, thereby substantially increasing the length of the wildfire season (Schoennagel et al., 2004; Oki, 2006; Westerling et al., 2006; Vörösmarty et al., 2010). Further, decades of fire suppression throughout the western US has resulted in an excess of fuels in many forests, which means that more fires are burning at high severity. As a result, ecosystems and communities within and downstream from forests prone to fire may face increasing adverse effects of wildfires. A better understanding of how both human and aquatic communities are impacted by wildfire is needed if we are to adapt human behavior, policy, management and watershed protection and restoration efforts related to forests, fire, and vulnerable aquatic ecosystems.

Wildfires threaten both rural and urban communities and have both short and long-term impacts on local economies. While immediate impacts on communities are usually negative, long-term effects may lead to either negative or positive economic development (Dale, 2010). Wildfires may affect rural and urban economies differently and increasing population growth within the wildland-urban interface places more people at rural fire risk than ever before (Murphy et al., 2018; Paveglio et al., 2015). A better understanding of how managers utilize information on economic impacts to make fire prevention and restoration decisions is necessary as the risk of wildfire increases (Prudencio et al., 2018).

In addition to affecting human communities, wildfires change physical landscape processes and alter aquatic habitats in the western US. Wildfires initiate hydrologic, geomorphic and ecological changes in watersheds by reducing rainfall interception and evapotranspiration and altering the soil infiltration capacity, leading to increases in the volume of water entering a river network, known as runoff. Current streamflow models indicate that wildfire is an important component when predicting streamflow volumes, but fail to identify relationships between changes in runoff and environmental variables (Wine et al., 2018). Additionally, models used to predict post-wildfire runoff are highly dependent on a single parameter, which is chosen, somewhat subjectively, by the modeler, leading to considerable uncertainty (Grove et al., 1990; Springer and Hawkins, 2005; Stuebe and Johnson, 1990; White, 1988). As wildfires increase, there is an urgent need for more accurate and accessible models to predict the change in the magnitude of runoff and peak floods after a fire, using readily available metrics, such as fire severity, soil type, and basin size.

Wildfires also change the sediment supply to rivers, thereby changing the grain size distribution on the riverbed and affecting aquatic communities, such as salmonids. Salmonids depend on various riverbed grain sizes at multiple stages of life, including: redd construction, embryo incubation, and alevin emergence (Kondolf, 2000). Wildfires can improve aquatic habitat by replenishing spawning gravels and introducing large boulders, which create favorable hydraulic environments (Sedell et al., 2015). However, they can also degrade habitat by burying spawning gravels and reducing pore space which can inhibit successful incubation and emergence (Gresswell, 1999; Propst and Stefferud, 1997; Roghair et al., 2002). Even though Western US mitigation efforts currently aim to maintain native salmonid populations, large declines in native salmonid populations are expected (Wenger et al., 2011; Williams et al., 2009). In order to stop these declines and enact effective restoration and mitigation policies, it is necessary to understand how wildfires change the riverbed grain size, and how those changes affect the quality of salmonid habitat.

This thesis uses a variety of datasets and analytical techniques to study the impacts of wildfire on human communities as well as river hydrology and geomorphology, with a specific focus on salmonid habitat conditions. This research improves our understanding of the challenges that human and aquatic communities face with increasing occurrence of wildfire, as well as highlights important benefits of wildfire. Specifically, this thesis explores a) general trends in wildfire throughout the western US and the economic effects of wildfire on rural and urban economies as well as perceptions of fire managers (Chapter 2); b) changes in runoff and peak flow post-wildfire (Chapter 3); and c) changes in riverbed grain size and how those changes affect the quality of salmonid habitat (Chapter 4). Understanding links between fire and the effects on communities and landscapes will help future predictive modeling efforts and thus aid in developing effective and efficient restoration and mitigation practices. In chapter 5, we synthesize the results of all three chapters and discuss future work that may help to further these results.

References

Cal Fire, n.d. Benefts of Fire. https://www.fire.ca.gov/media/5425/benifitsoffire.pdf

Dale, L., 2010. The True Cost of Wildfire in the Western US, in: West for Leadersh Coalit: Lakewood, CO, USA.

Gresswell, R.E., 1999. Fire and Aquatic Ecosystems in Forested Biomes of North America. Trans. Am. Fish. Soc. https://doi.org/10.1577/1548-8659(1999)128<0193:FAAEIF>2.0.CO;2

Grove, M., Harbor, J., Engel, B., 1990. Composite vs. distributed curve numbers: effects on estimates of storm runoff depths. J. Am. Water Resour. Assoc. 34, 935–941.

Kondolf, G.M., 2000. Assessing Salmonid Spawning Gravel Quality. Trans. Am. Fish. Soc. 129, 262–281. https://doi.org/10.1109/LCOMM.2018.2864265

Murphy, B.P., Yocom, L.L., Belmont, P., 2018. Beyond the 1984 Perspective: Narrow Focus on Modern Wildfire Trends Underestimates Future Risks to Water Security. Earth's Futur. 6, 1492–1497. https://doi.org/10.1029/2018EF001006

Paveglio, T.B., Brenkert-Smith, H., Hall, T., Smith, A.M.S., 2015. Understanding social impact from wildfires: Advancing means for assessment. Int. J. Wildl. Fire 24, 212–224. https://doi.org/10.1071/WF14091

Propst, D.L., Stefferud, J.A., 1997. Population dynamics of Gila trout in the Gila River drainage of the south-western United States. J. Fish Biol. https://doi.org/10.1006/jfbi.1997.0512

Prudencio, L., Choi, R., Esplin, E., Ge, M., Gillard, N., Haight, J., Belmont, P., Flint, C., 2018. The Impacts of Wildfire Characteristics and Employment on the Adaptive Management Strategies in the Intermountain West. Fire 1, 46. https://doi.org/10.3390/fire1030046

Roghair, C.N., Dolloff, C.A., Underwood, M.K., 2002. Response of a Brook Trout Population and Instream Habitat to a Catastrophic Flood and Debris Flow. Trans. Am. Fish. Soc. 131, 718–730. https://doi.org/10.1577/1548-8659(2002)131<0718:ROABTP>2.0.CO;2

Schoennagel, T., Veblen, T. T., Romme W. H., 2004. The Interaction of Fire, Fuels, and Climate across Rocky Mountain Forests. Bioscience 54, 661. https://doi.org/10.1641/0006-3568(2004)054[0661:TIOFFA]2.0.CO;2

Sedell, E.R., Gresswell, R.E., Mcmahon, T.E., 2015. Predicting spatial distribution of post fi re debris fl ows and potential consequences for native trout in headwater streams. Freshw. Sci. 34, 1558–1570. https://doi.org/10.1086/684094.

Springer, E.P., Hawkins, R.H., 2005. Curve Number and Peakflow Responses Following the Cerro Grande Fire on a Small Watershed 836, 1–12. https://doi.org/10.1061/40763(178)40

Stuebe, M., Johnson, D.M., 1990. Runoff volume estimation using GIS techniques. Water Resour. Bull. 26, 611–620.

Wenger, S.J., Isaak, D.J., Luce, C.H., Neville, H.M., Fausch, K.D., Dunham, J.B., Dauwalter, D.C., Young, M.K., Elsner, M.M., Rieman, B.E., Hamlet, A.F., Williams, J.E., 2011. Flow regime, temperature, and biotic interactions drive differential declines of trout species under climate change. Proc. Natl. Acad. Sci. 108, 14175–14180. https://doi.org/10.1073/pnas.1103097108

Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase Western U.S. forest wildfire activity. Science (80-.). 313, 940–943. https://doi.org/10.1126/science.1128834

White, D., 1988. Grid-based application of runoff curve numbers. J. Water Resour. Plan. Manag. 114, 601–612.

Williams, J.E., Haak, A.L., Neville, H.M., Colyer, W.T., 2009. Potential Consequences of Climate Change to Persistence of Cutthroat Trout Populations. North Am. J. Fish. Manag. 29, 533–548. https://doi.org/10.1577/m08-072.1

Wine, M.L., Makhnin, O., Cadol, D., 2018. Nonlinear Long-Term Large Watershed Hydrologic Response to Wildfire and Climatic Dynamics Locally Increases Water Yields. Earth’s Futur. 6, 997–1006. https://doi.org/10.1029/2018EF0009

CHAPTER 2

THE IMPACTS OF WILDFIRE CHARACTERISTICS AND EMPLOYMENT ON THE ADAPTIVE MANAGEMENT STRATEGIES IN THE INTERMOUNTAIN WEST[1]

Abstract

Widespread development and shifts from rural to urban areas within the Wildland-Urban Interface (WUI) has increased fire risks to local populations, as well as introduced complex and long-term costs and benefits to communities. We use an interdisciplinary approach to investigate how trends in fire characteristics influence adaptive management and economies in the Intermountain Western US (IMW). Specifically, we analyze area burned and fire frequency in the IMW over time, how fires in urban or rural settings influence local economies, and whether fire trends and economic impacts influence managers' perspectives and adaptive decision-making. Our analyses showed some increasing fire trends at multiple levels. Using a non-parametric event study model, we evaluated the effects of fire events in rural and urban areas on county-level private industry employment, finding short- and long-term positive effects of fire on employment at several scales and some short-term negative effects for specific sectors. Through interviewing 20 fire managers, we found that most recognize increasing fire trends and that there are both positive and negative economic effects of fire. We also established that many of the participants are implementing adaptive fire management strategies, and we identified key challenges to mitigating increasing fire risk in the IMW.

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1. Introduction

Wildfires pose an increasing threat to communities and built infrastructure throughout the Western United States. Over the last four decades in the Western U.S., the total annual area burned has increased considerably with wildfires occurring at higher frequency [1, 2]. Since the mid-1980s, warmer temperatures and increased aridity have increased the fire season by ca. 78 days in this region [1, 3]. Previous research on broad regional fire trends has primarily focused on the entire Western U.S. However, the Intermountain West (IMW) – defined in this paper as consisting of Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming – differs from the coastal parts of California, Oregon, and Washington in that the IMW states overall are largely characterized by relatively dry conditions and arid vegetation communities that make it especially vulnerable to large, high-severity fires [4–7]. This susceptibility to fire is expected to increase under warmer and more arid future climate scenarios [8]. While extensive work on fire has been conducted within this region [2, 4], a better interdisciplinary understanding of fire trends at multiple scales within this expansive, ecologically-distinct portion of the West is needed if we are to adapt human behavior for more effective fire management in the face of a changing climate.

In addition to climatic factors driving increases in wildfire, widespread development along the wildland-urban interface (WUI) – the transition zone where housing meets or is intermixed with undeveloped vegetated areas – has increased populations and values at risk [9–12]. Population in the Western U.S. has grown rapidly in recent decades [13], with substantial development and housing growth concentrated in the WUI [11, 12, 14]. With greater expansion into the WUI and increased fire frequency, more people are exposed to property loss, especially in high density urban regions. Research also shows that closer proximity to the WUI leads to higher suppression costs [15, 16]. However, the distribution of wildfire risks and the capacity to mitigate them varies between urban and rural communities [17, 18]. Rural communities, which are more prevalent in the IMW, may be differentially affected by wildfire due to fundamental differences in socioeconomic characteristics, including a greater dependence on natural resource and recreation-based industries [17, 19, 20]. Furthermore, rural communities have limited financial resources compared to urban areas [17], although residents have been more willing to participate in suppression tactics to protect their livelihoods [20, 21].

While wildfire can physically threaten urban and rural communities, it can also have immediate and long-term consequences for local economies. The majority of short-term economic impacts of wildfire tend to be negative, such as the costs associated with firefighting, property damage, and loss of timber resources, in addition to the evacuation of local residents, impaired water and air quality, and loss of tourism, business, and recreation revenue [22]. In the long-term, wildfire may increase economic volatility or lead to unstable economic growth in the year following a fire [23]. However, wildfire may also have positive impacts in some employment sectors from increased construction of infrastructure and rebuilding of homes, restoration of forest and aquatic ecosystems, and greater opportunities for resource extraction, like salvage logging [24]. These economic costs of fire are expected to increase with changing climate conditions and greater development in wildland areas. While studies have investigated a variety of economic impacts of fire, there is still a need for a greater understanding of how managers utilize information on these impacts to make decisions and fire mitigation policy [25]. As increased risk of fire exacerbates socioeconomic effects on communities, it is critical to understand how wildfire impacts manager perspectives and adaptive management strategies to better mitigate those risks in an uncertain future [26].

With greater development in the more fire-prone wildland and WUI areas, fire managers have been tasked with greater responsibility for the protection of private citizens in increasingly vulnerable areas. Various factors influence fire managers' decisions, including fire characteristics (e.g., fire size and frequency), expectations of affected communities and government officials, and federal fire management policy [27]. Challenges to these decisions include natural accumulation of biofuels over time, projected (if uncertain) increases in aridity in those accumulating fuels, conflicting management objectives by different resource agencies, social and political pressures to immediately suppress fire, and managing the short- and long-term cumulative impacts of fire [27–30]. Overall, the complex decision-making process for fire managers is not well understood [25]. Improving our understanding of the various influences, needs, and challenges for management decisions answers the need for increased integration of fire management into the decision-making and risk management literature [28, 31].

An interdisciplinary approach is needed to more fully understand the complex systems and consequences of wildfire in changing socio-demographic and resource management contexts [18, 32]. Responding to changes in the wildfire regime in an adaptive way requires managers to understand broader trends in wildfire characteristics over a variety of scales, understand the condition of the forest and fuels within their management domain, and also discern highly contextual information from affected communities such as economic impacts and expectations of officials and community members. Integrating quantitative and qualitative data and analytical methods on physical and social aspects of fire advances understanding of wildfire trends and impacts.

We applied an interdisciplinary approach to investigate how recent trends in fire characteristics influence regional adaptive management in the rural and urban areas of the IMW, exploring three interrelated questions: 1) Are area burned and fire frequency increasing within the IMW?; 2) Do fires in urban or rural settings influence employment trends in local economies, and if so, how?; and 3) Do trends in fire characteristics and economic impacts of fire influence perspectives of managers and adaptive decision-making, and if so, how? We addressed these questions by quantifying fire characteristics and economic impacts and connecting them with qualitative interviews of fire managers from three regions within the IMW. Our study identifies key challenges to implementing adaptive fire and forest management strategies for both short- and long-term fire risk mitigation (Figure 2-1).

2. Materials and Methods

We evaluated area burned and fire frequency for large fires across all eight IMW states. Using the 2011 National Land Cover Database and boundaries from the U.S. Census Bureau, we first quantified the amount of “burnable area” of each county (n = 281) within each state as the sum of all land cover types excluding open water, salt flats, and barren land (www.mrlc.gov) [33, 34]. We downloaded spatial data depicting the perimeters of individual fires greater than ~400 ha that burned within the region over a 32-year period

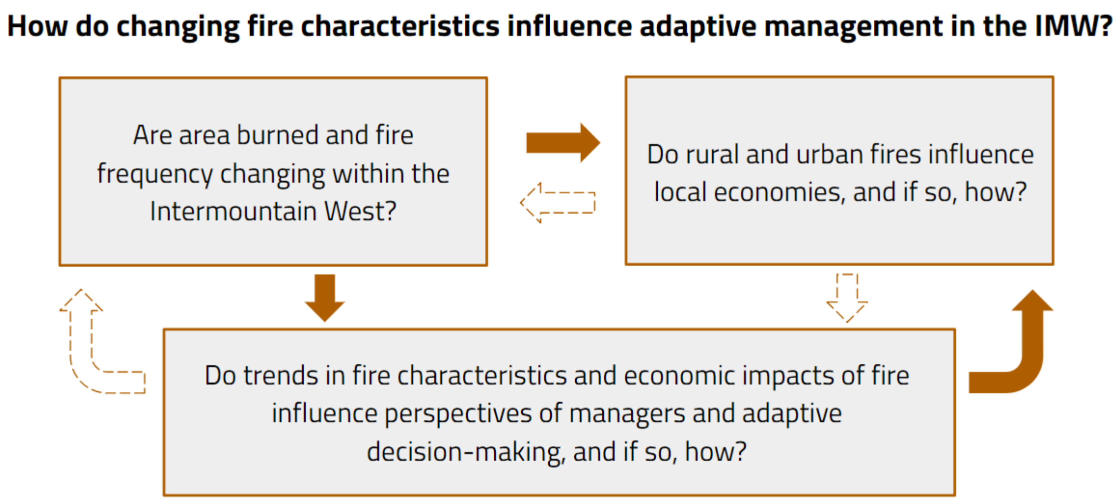

Figure 2-1. We address the overarching research question (top in bold) through investigating the sub-questions in the three boxes. The solid arrows show the connections that this interdisciplinary study addresses and are further discussed later in the paper. We acknowledge that other feedbacks exist between these questions (dashed arrows), such as managers' decisions and economies impacting fire trends.

(1984-2015) from the Monitoring Trends in Fire Severity (MTBS) database (www.mtbs.gov) [35]. We obtained spatial data that delineates the WUI based on housing density and wildland vegetation cover at the census block scale from the SILVIS Lab (http://silvis.forest.wisc.edu/maps/wui) [9]. Fires that occurred within 2.4 km [14, 36] of areas defined as "high housing density" (> 741.3 housing units km^{-2}) were classified as "urban fires", while those that occurred outside of the buffer were designated as "rural fires" (Figure 2-2). In other words, "urban fires" refer to high-density WUI fires, and "rural fires" refer to low-density WUI fires. The buffer we implemented is intended to represent the distance at which urban structures are likely to become a primary concern, which may influence the vigor or strategy employed by fire suppression efforts [36].

To assess trends in area burned and fire frequency over the 32-year period at regional, state, and county levels, we calculated linear regressions in the R statistical computing environment [37]. Linear regression was used as the most conservative

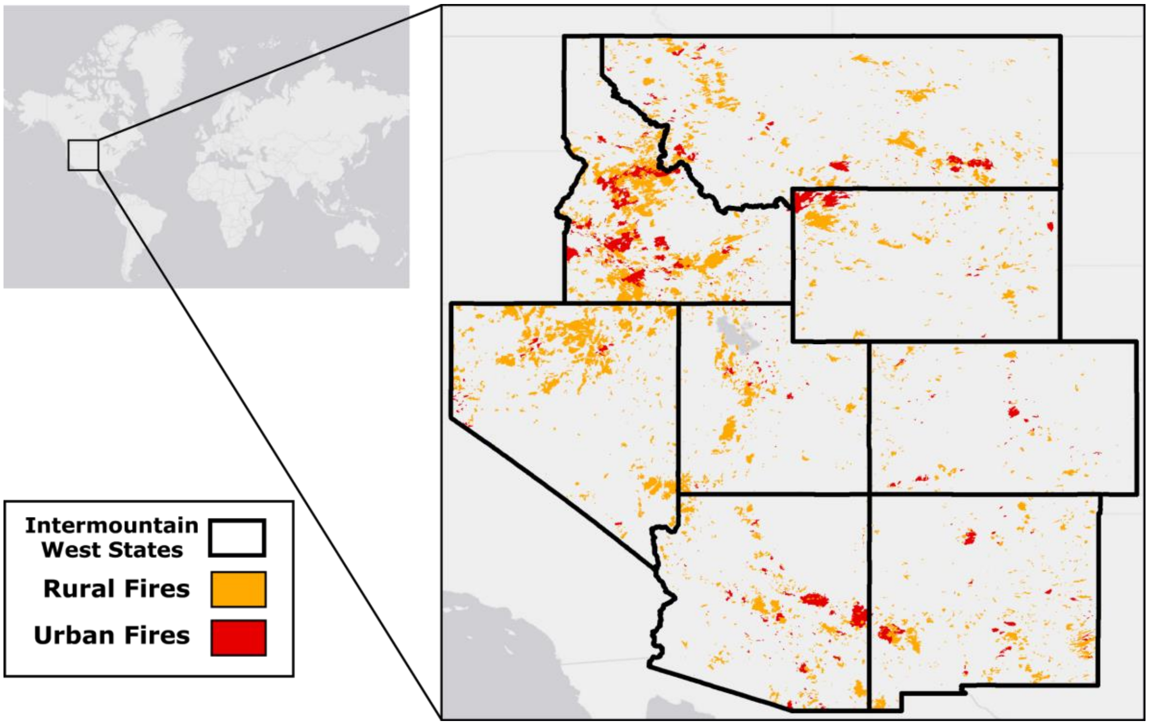

Figure 2-2. Fires over ~400 ha over a 32-year period (1984-2015), broadly classified as either "urban" (< 2.4 km from high-density census-blocks) or "rural".

approach to finding increasing or decreasing trends in the fire data shown in the supplementary information (Figures S1-S5). Researchers have compared various approaches when modeling big data trends and have found linear fit to be appropriate for general overall trends [38]. For analyses of area burned, we summed the burned areas within each spatial unit (region, state, or county) by year and then normalized these values by dividing by burnable area within that unit, assessing trends in the percentage of each unit burned. For regional and state-level trends in fire frequency, we based annual fire counts on the number of fire perimeter centroids (i.e. centers) falling within each state to avoid double-counting fires that crossed state lines. For county-level frequency trends, fire counts were represented by the total number of fire perimeters intersecting each county boundary. We tested for the significance of linear trends separately for rural and urban fires at both the regional and state-level, for both area burned and fire frequency.

To focus a portion of our economic analysis and our qualitative interviews with managers in areas that have experienced increasing trends in burned area and/or fire frequency, we identified focal counties by considering the steepness of the linear regression slopes for area burned and fire frequency in each county. Focusing on the top 5% of all regression slopes for all counties and excluding counties with increasing trends driven by outliers using a visual test, we identified 14 counties (Figure 2-3). We refer to these 14 counties as the “Increasing Focal Counties” throughout the rest of this paper. For more context on these “Increasing Focal Counties”, six counties had increasing trends for burned area and twelve had increasing trends for fire frequency. This equated to a linear trend line slope greater than 7% for counties identified as our Increasing Focal Counties.

We estimated the impacts of urban and rural wildfires on local economies by analyzing changes in the employment rate in affected counties after each wildfire event. Our economic analysis looks at employment and fire data from 2001-2015, due to the employment data only being available from these years. We utilized monthly data from on local employment rates from the Bureau of Labor Statistics (BLS) [39], retrieved online using the R package ‘blsAPI’ (https://CRAN.R-project.org/package=blsAPI). We then analyzed employment in relation to MTBS data on fire ignition date, fire size and location, and to our rural and urban fire classifications. We focused on five BLS employment datasets broken into three hierarchical tiers of employment specificity that range from broad to more specific sectors. The broadest category included (I) Total

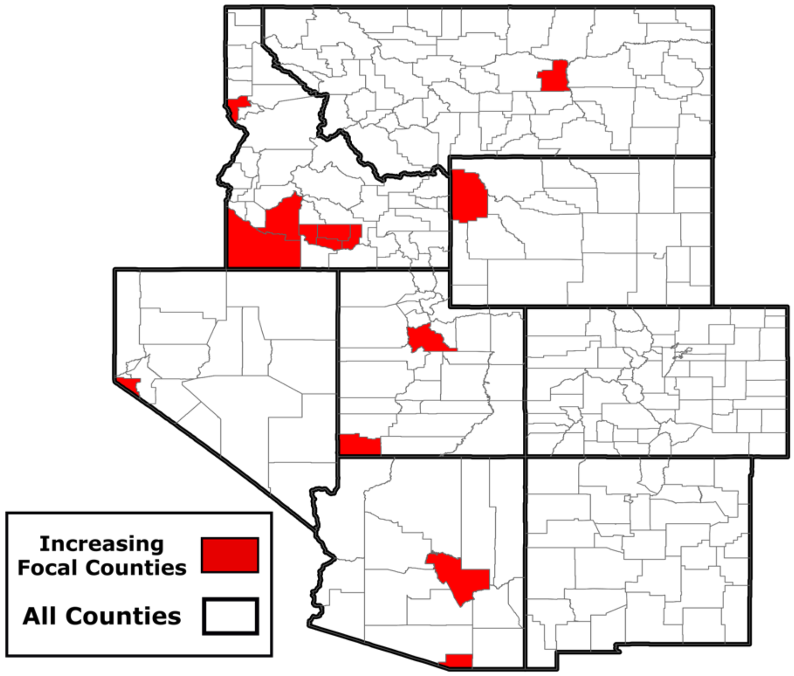

Figure 2-3. Increasing Focal Counties (Arizona [n=2], Idaho [n=7], Montana [n=1], Nevada [n=1], Utah [n=2], and Wyoming [n=1]) have experienced increasing trends for area burned, fire frequency, or both from 1984-2015. When ranking the 281 counties' regression slopes from highest to lowest, the Increasing Focal Counties are in the top 5 percent of slopes.

Employment for all IMW states (n=281 counties). The BLS divided Total Employment into two sub-categories: (1) Goods Producing, and (2) Service Providing sectors. Within each of the (1) Goods Producing and (2) Service Providing sub-categories, we further evaluated the (1a) Natural Resource and Mining, and (2a) Leisure and Hospitality sub-sectors, respectively. Each category contains monthly employment data from 2001-2015 at the county level (for a sub-sector employment example, see Figure 2-4). Graphs of employment data with the fire data used in our economic analyses can be found in the supplementary materials (Figures S1-S5).

We acknowledge that wildfires can have a wide range of economic impacts, including permanent loss of property or infrastructure, temporary loss of use or degradation, impacts on water, soil and forest resources, positive and negative impacts on

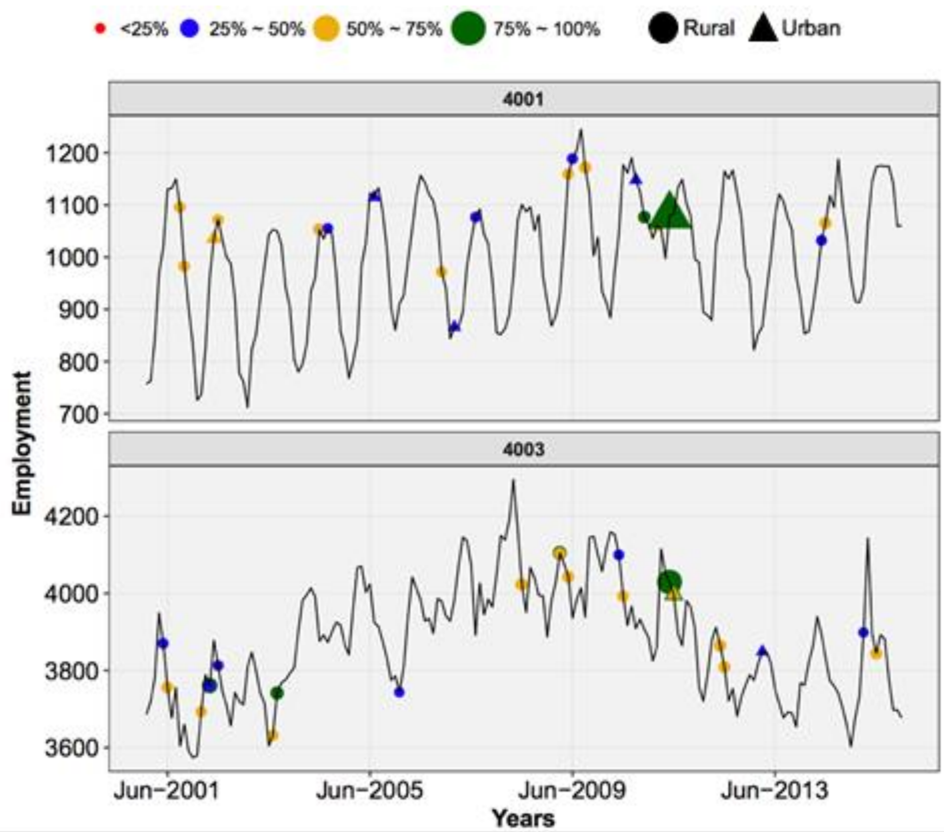

Figure 2-4. Example from two Arizona counties (Apache County - FIPS 4001; Cochise County - FIPS 4003) showing employment trends for the Leisure and Hospitality sector (2001-2015). Triangles represent urban fires, while dots represent rural fires. Different sizes of dots or triangles represent differing fire size. Fires were sorted according to size. Green dots/triangles represent the upper 25th percentile of fires, followed by the 50th-75th percentile in blue, and lower 25th percentile in red.

terrestrial and aquatic wildlife, as well as costs of fire suppression and post-fire restoration. While data were not available to quantify those factors at the scale of our analysis, we suggest that future efforts seek to compile or estimate such data for a more comprehensive analysis of economic impacts of wildfire.A central innovation of our study is the development of a new data set linking labor statistics data with MTBS fire data and the WUI classification. Nielsen-Pincus et al. (2013) studied the different impacts of urban and rural wildfire on local economies using the United States Department of Agriculture (USDA) Economic Research Service county typology to identify the rural and urban counties [23]. However, the majority of IMW fires from the MTBS database did not cover the entire county and often crossed county and/or state lines. This creates false classifications in cases where fires occur in the urban parts of counties labeled 'rural' and vice versa. Therefore, the USDA county classifications did not have sufficient resolution for our purposes. Thus, we utilized our much higher resolution WUI urban and rural fire classification to obtain a finer spatial resolution of fire types, and used fire ignition date, location, and size from MTBS database to identify each wildfire that happened in IMW from 2001 to 2015. Our classified fire database is available as supplementary information associated with this paper.

We used an event study framework to analyze the different impacts of rural and urban fires on the employment of affected communities. Taking total employment rate for all industry as an example, the event study model gives us the change in employment rate within a county after a wildfire event,

$$log\, E_{c,t}^{total} = \sum_{j=-6}^{6} \gamma_j D_{s,t-j} + \; Acres + Trends + \mu_c + \mu_s + \delta_m + \varepsilon_{c,t}$$

where $logE_{c,t}^{total}$is the dependent variable, representing the percent changes in total employment rate for county *c* at time *t*. The variable $D_{s,t-j}$ is the fire indicator, equal to 1 if the county is reported to have experienced wildfire in month *t*, according to the MTBS dataset. The month of wildfire ignition corresponds to (*j*=0). We normalized the effect in the month before the fire (*j*=1) to zero. $Acres$ represents the area burned (acres) in each event, to address how the size of fires can affect the local labor market. $Trends$ represents the overall trend of the regional total employment, to help account for broader economic trends of the region that may impact employment. County fixed effects, represented by μ_c, standardize the comparison by only comparing within the same county. Variable μ_s represents the year fixed effects, thus we are only comparing impacts within the same year. Variable δ_m is the month fixed effects, while $\varepsilon_{c,t}$ shows the error term. Employment numbers can vary due to various factors, including differences in industries between counties, economic trends during different years, and changes across employment across months and seasons. These county, year, and month fixed effects help control for these changes in employment across different counties, across different years, and across different months of the year.

The model assumes that the occurrence of a fire is a random event, conditional to fire location and monthly time of year, and is uncorrelated with unknown confounding variables. We chose a 6-month event window to observe the impact of fire over time to be consistent with the seasonal trend of the BLS and fire data (Figure 2-4), both of which occur on a 6-month interval. Previous research has found longer-term lagged effects to be important when studying labor markets after fire [40, 41]. Therefore, we ran our model with a 12-month event window as well, which are also discussed briefly in the results section below. We ran the model for the five different employment sectors, defined above, and four regressions: All Fires (including all rural and urban fires within all counties), Rural Fires (including rural fires within all counties), Urban Fires (including all urban fires within all counties), and Increasing Focal Counties (rural and urban fires within the 14 counties that were classified above as experiencing increasing fire trends).

From our 14 Increasing Focal Counties (Figure 2-3), we focused our interviews in three geographic regions with clustered counties: two in Arizona, two in Utah, and six counties clustered in southwestern Idaho. We used the three regions as focused case studies that helped qualitatively illustrate fire manager challenges. We recognize that these findings are not necessarily representative of the entire IMW region, but offer in-depth insight into regional perspectives. We used criterion and snowball sampling to conduct key informant interviews in March and April of 2018 (Utah State University Institutional Review Board Exempt Protocol #9130). We took a qualitative approach to collecting thematic interview data. While we had a small sample size of total interviews, others have utilized a similar thematic analysis [42] that identified social characteristics at the community level. Thematic analysis is an effective coding strategy that identifies common elements among participants around a specific topic and summarizes coded statements into broader themes [43].

To identify potential participants, we contacted agencies whose fire management jurisdictions were within or overlapping the specified counties in Arizona, Idaho, and Utah and sought participants whose job responsibilities included managing wildland fire through response, planning, mitigation, and prevention. To increase our sample pool, we asked potential participants for references of other key informants in their area. Using these techniques, we conducted 20 semi-structured interviews of managers from different state, tribal, and federal agencies. We primarily interviewed District Rangers, Fire Management Officers, and Fuels Specialists, all with a wide array of work history and experience. Interviews lasted between 16 and 86 min (mean = 39 min). Nineteen interviews were audio recorded with consent of the participant. One participant opted to have notes taken instead of an audio recording. This interview was fully transcribed from the notes within 24 hours. All audio recorded interviews were transcribed and then checked for accuracy by the interviewer.

While the interviews were structured in that each participant was asked the same set of questions in the same order, they were conducted in a manner to encourage free expression and explanation of participants' perspectives on 1) local fire history and fire trends, 2) economic effects of wildfire, 3) influences on their local fire management and adaptation practices, and 4) challenges to wildfire risk mitigation (for the full interview protocol, see Table 2-1). Interviewers avoided prompting with cues to prevent priming participants responses. A thematic analysis approach was implemented, emphasizing semantic coding of explicit words used by participants to answer each question [43, 44]. Interview content was analyzed for emergent themes by the following four-step process to ensure reliable interpretations: 1) interviewers read through corresponding transcripts for accuracy; 2) interviewers read assigned transcripts and summarized the content for each interview according to key research questions; 3) a second interviewer read the transcripts and corresponding summaries to check for accuracy; and 4) interviewers and transcribers reviewed and coded summaries for major themes together while referring back to original transcripts as needed to resolve coding questions or disagreements. By this process, all transcripts were analyzed qualitatively for major themes by at least two people to increase the reliability of interpretations. During coding, the number of participants who mentioned different topics were noted for reporting major themes and corresponding responses. Managers' responses were also analyzed for possible geographic patterns as part of the thematic analysis. While participants were selected to collective represent fire manager perspectives within the three focus areas in Idaho, Utah, and Arizona, we do not suggest they are necessarily representative of the larger Intermountain West region as a whole.

Table 2-1. Interview questions for participants regarding their perspectives on what influences their management practices and decisions.

Opening & Background Questions
How long have you been working for __________ in a management position?
What is the scope of your position?
How does your work relate to fire management?
In your opinion, has the frequency of wildfires or area burned changed in your area? If yes, how so?
Has wildfire influenced economies in your area? If so, how?
Influences and Challenges
Do economic impacts of fire influence your management decisions? If so, how?
Have past fires or changes in fires over time affected your current management policies and decisions? If so, how?
What challenges do you face in order to effectively mitigate wildland fire risk?
Community and Institutional Expectations
What does the local community expect from your fire management decisions?
What do government officials expect from your fire management decisions?
Local Policy Influence
Do you have a current official fire management plan? (e.g. CWPP, CPAW) [Probe for description]
Is this plan implemented into your routine management practices? If so, how?
Decision-Making
Has any change in fire frequency or burned area influenced your management decisions and adaptive practices? If so, how? If not, why not?
Do you think any future changes or events might lead to changes in fire management and policy for [your agency]? If so, what kind of changes or events might have more of an impact on fire management practices or policies?
Do you manage fires in rural versus urban areas differently? If so, how? Would any change in fire frequency or burned area influence how you manage fires in rural versus urban areas? If so, how?
Do economic effects of fire influence how you manage rural versus urban areas? If so, how?
Were there any particular fires that changed your approach to or thinking about fire management?

3. Results

3.1. Changes in area burned and fire frequency within the IMW

Our analysis of MTBS historical fire data shows that fire characteristics have changed heterogeneously throughout the IMW. From 1984 to 2015, there were 5,569 large wildfires in the IMW, 515 of which we classified as urban and 5,054 as rural. At the regional scale, there is a significant increase in area burned by rural fires ($p < 0.1$) (Table 2), while focusing at the state level shows important variations in trends associated with area burned and fire frequency and are often driven by significant burn events or fire-prone areas. Fire frequency has also increased in both rural ($p < 0.1$) and urban fires ($p < 0.05$) (Table 2). Area burned increased significantly within 28/281 counties and fire frequency increased within 22/281 counties ($p < 0.05$). When we relaxed the p-value to $p < 0.10$, 44/281 counties increased in area burned, and 42/281 counties increased in fire frequency. At the state scale, Arizona and Colorado have significantly increased in burned area for rural fires ($p < 0.05$) (Table 2; Figure 2-5). New Mexico ($p < 0.05$) and Idaho ($p < 0.1$) show significant increasing trends for area burned by urban fires (Table 2-2; Figure 2-5). Wyoming depicts a slight significant decreasing trend ($p < 0.1$) in area burned by urban fires (Table 2-2; Figure 2-5). In contrast, fire frequency has significantly increased for rural fires in Arizona ($p < 0.05$) and Montana ($p < 0.1$) (Table 2-2; Figure 2-6). The apparent decreasing trend in area burned in Wyoming may be due to a historically large fire in Yellowstone National Park in 1988, which occurred at the beginning of our fire record and skewed the overall result. The same data, fit with the LOESS curve, are available in supplementary information (Figures S6 and S7).

3.2. Economic Impacts of Fire

Fire can have a wide array of influences on local economies, including impacts on employment, property and infrastructure, air, water and soil quality, human health, costs associated with fire suppression or post-fire restoration, timber harvest, and tourism [22–24]. In this paper, we focus on employment as data are not available to quantify other

Table 2-2. Regression slopes for area burned and fire frequency in both rural and urban areas. Significance is denoted at the p < 0.1 (*) and at the p < 0.05 (**) values.

	Area Burned		**Fire Frequency**	
	Rural	*Urban*	*Rural*	*Urban*
IMW	0.007*	0.002	2.834*	0.377**
AZ	0.009**	0.005	0.783**	0.032
CO	0.004**	0.001	0.209	0.046
ID	0.019	0.013*	0.590	0.040
MT	0.005	0.003	0.882*	0.022
NM	0.007	0.006**	0.240	0.069
NV	0.008	0.000	0.040	0.012
UT	0.007	0.001	0.241	0.028
WY	-0.001	-0.024*	0.349	0.038

impacts at the broad scale of our study. Employment data are readily available at a county scale in our time period and are evaluated monthly. As mentioned in the methods section above, we focused on a 6-month window after fires, because our employment and fire data indicated a 6-month cycle (Figure 2-4). However, since other studies also find other significant effects after 6 months, we ran a 12-month model as well and included the results as supplementary materials (Tables S1-S5). The results between the 6-month model and the 12-month model are similar, with most significant effects showing within the first 6 months. There are a few positive significant effects at the end of the 12-month model, which indicates potential longer-lagged effects on employment.

Total Employment (I) results generally yielded positive effects of fires for all four sets of regressions: All Fires, Rural Fires, Urban Fires and Increasing Focal Counties (Table 2-3). Rural Fires and Urban Fires had differing impacts on affected county labor markets. Rural Fires had greater positive short-term impacts on affected county employment rate, and were all statistically significant at the 90% level. In contrast, Urban

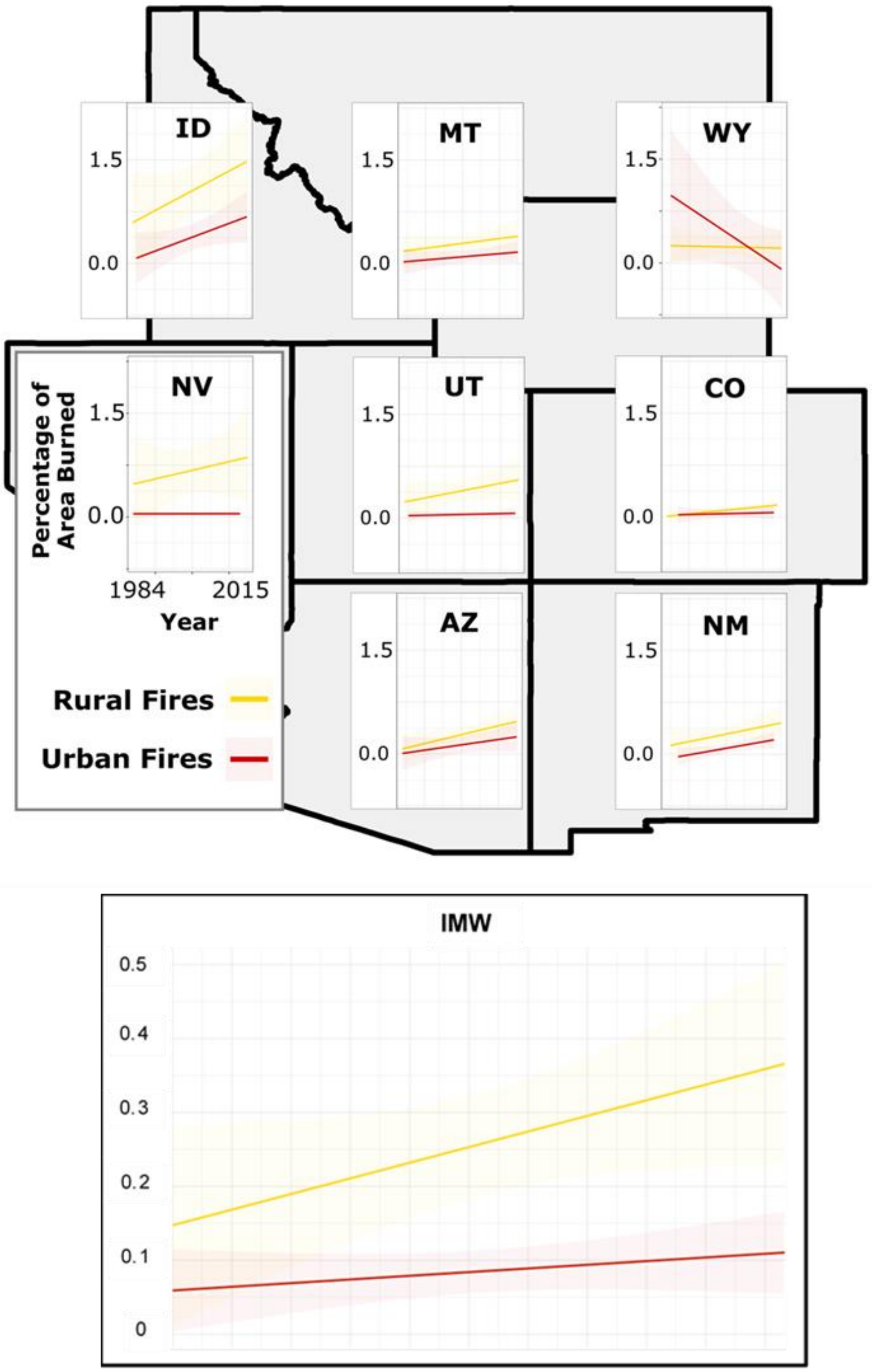

Figure 2-5. State-level linear trends in percentage of area burned for rural and urban fires.

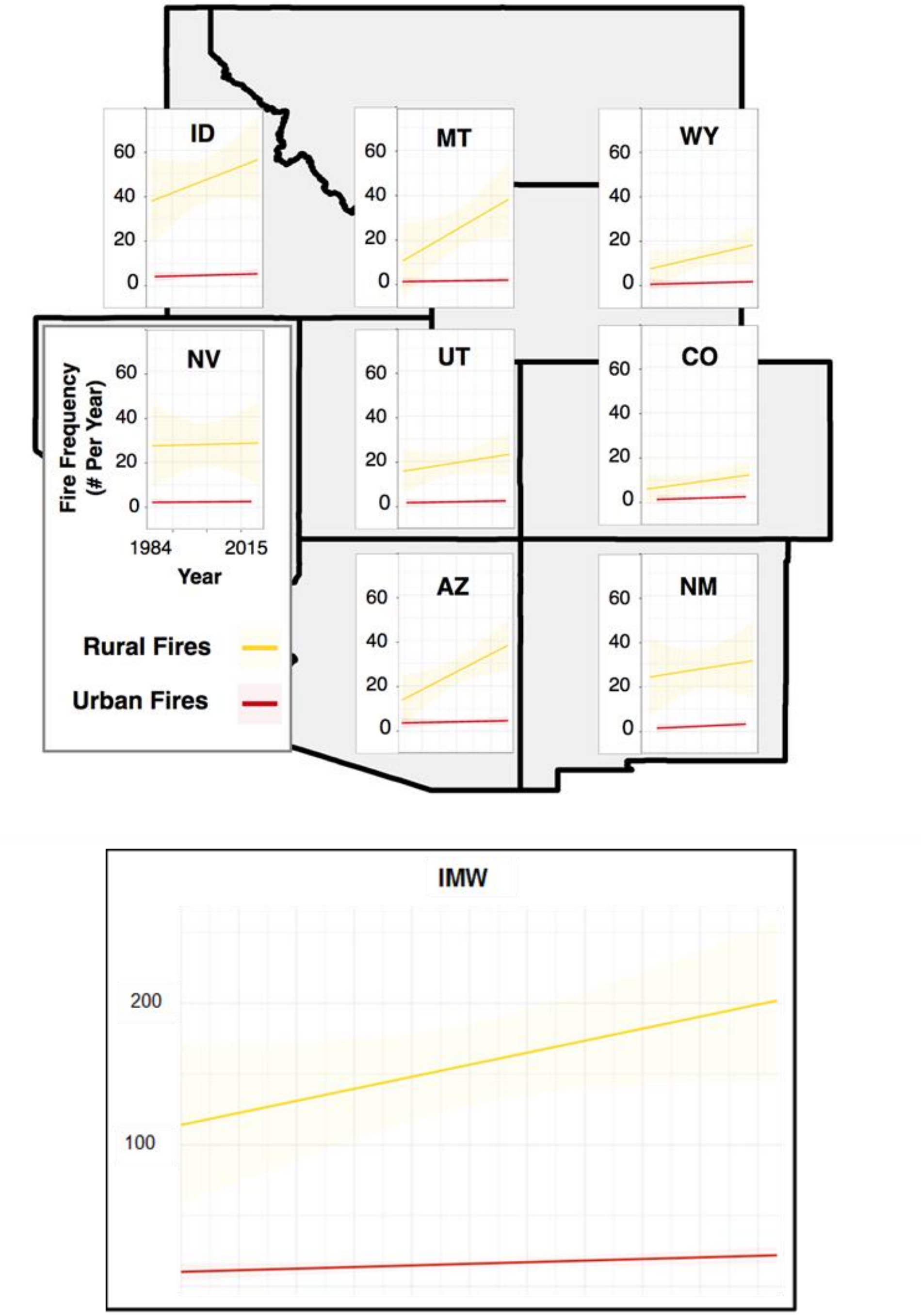

Figure 2-6. State-level linear trends in fire frequency for rural and urban fires.

Fires did not have a statistically significant impact on employment at the county level. We observed statistically significant increases for 4 months after a fire event when considering both All Fires and Rural Fires. For Increasing Focal Counties that we identified as having increasing area burned and/or fire frequency, we found statistically significant positive impacts up to 2 months after fire occurrence (Table 2-3). Overall, the impacts were lower for total employment than the sub-sectors, which are discussed in depth below. However, the duration of these impacts was longer for total employment.

Table 2-3. Regression results for (I) Total Employment for the 6-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). The first column presents the results for All Fires within all 281 IMW counties (44,666 observations), the second column represents the results for Rural Fires (44,360 observations), the third column represents the results for Urban Fires (41,429 observations), and the last column represents the results for the 14 Increasing Focal Counties (2,274 observations). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable Effects of Fires on Employment (%)			
	All Fires	**Rural Fires**	**Urban Fires**	**Increasing Focal Counties**
Fire Happened	0.012***	0.013***	-0.001	0.026***
	(0.003)	(0.003)	(0.008)	(0.007)
1 Months After	0.005*	0.005**	-0.007	0.012*
	(0.003)	(0.003)	(0.007)	(0.006)
2 Months After	0.006**	0.006**	-0.001	0.012*
	(0.003)	(0.003)	(0.007)	(0.006)
3 Months After	0.005*	0.005*	0.0001	0.004
	(0.003)	(0.003)	(0.007)	(0.006)
4 Months After	0.006**	0.005*	0.002	0.003
	(0.003)	(0.003)	(0.007)	(0.006)
5 Months After	0.002	0.002	0.006	-0.005
	(0.003)	(0.003)	(0.007)	(0.006)
6 Months After	0.002	0.001	0.007	-0.001
	(0.003)	(0.003)	(0.007)	(0.006)
Observations	44,666	44,360	41,429	2,274
R^2	0.996	0.996	0.996	0.996
Adjusted R^2	0.996	0.996	0.996	0.996
Residual Std. Error	0.115 [df=44,345]	0.115 [df=44,039]	0.116 [df=41,109]	0.101 [df=2,220]

3.2.1. Fire Impacts on (1) Goods Producing & (2) Service Providing Sectors

We observed significant positive impacts for All Fires and Rural Fires for both (1) Goods Producing and (2) Service Providing sectors (Table 2-4), but the impact decreases with each subsequent month post-fire. When we compared impacts between the (1) Goods Producing and (2) Service Providing sectors, the positive impacts were greater in the Goods Producing sector immediately during and 1 month after a fire (Table 2-4 and Table 2-5). The Increasing Focal Counties with increasing fire trends had the greatest total positive impact for the (1) Goods Producing sector during the month of fire ignition. However, when these results were compared to the (I) Total Employment regression results, these positive impacts were observed for a shorter period, less than 1 month post-fire.

3.2.2. Fire Impacts on (1a) Natural Resource and Mining & (2a) Leisure and Hospitality Sectors

Employment in the (1a) Natural Resource and Mining sector for All Fires, Rural Fires, and Increasing Focal Counties all had statistically significant positive labor impacts for the month when a fire was ignited (Table 2-6). The (2a) Leisure and Hospitality sector only had positive impacts two months after fire ignition for Rural Fires, but these impacts are not large, had a low significance level, and declined over time (Table 2-7). Negative impacts for employment in the (2a) Leisure and Hospitality sector were observed in Urban Fires one month after ignition. For Increasing Focal Counties, negative impacts were observed for (2a) Leisure and Hospitality sector during the month of fire ignition and 5 months post-fire.

Table 2-4. Regression results of the (1) Goods Producing sector for the 6-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable Effects of Fires on Employment (%)			
	All Fires	**Rural Fires**	**Urban Fires**	**Increasing Focal Counties**
Fire Happened	0.024***	0.025***	0.004	0.045***
	(0.005)	(0.005)	(0.015)	(0.012)
1 Months After	0.009*	0.010*	-0.001	0.012
	(0.005)	(0.005)	(0.014)	(0.010)
2 Months After	0.007	0.008	0.001	0.017
	(0.005)	(0.005)	(0.014)	(0.011)
3 Months After	0.006	0.007	0.004	0.017
	(0.005)	(0.005)	(0.014)	(0.011)
4 Months After	0.009	0.010*	0.008	0.017
	(0.005)	(0.005)	(0.014)	(0.011)
5 Months After	0.006	0.007	0.010	0.005
	(0.005)	(0.005)	(0.014)	(0.011)
6 Months After	0.007	0.007	0.005	-0.003
	(0.005)	(0.005)	(0.014)	(0.010)
Observations	44,165	43,877	40,966	2,209
R^2	0.984	0.984	0.984	0.977
Adjusted R^2	0.984	0.984	0.984	0.976
Residual Std. Error	0.223	0.223	0.224	0.168
	[df=43,844]	[df=43,556]	[df=40,647]	[df=2,155]

3.3. Qualitative Interview Results

Overall, 15 participants from the three areas chosen for further investigation recognized that area burned or fire frequency increased in their jurisdictions over the last 30 years. Within the positive responses, two managers said fire frequency is increasing, five managers said area burned is increasing, and eight managers said both are increasing. Four managers responded with “It Depends” and cited the nuances of time period and specific area, which may span different jurisdictions and counties. When managers’ responses were compared with the calculated fire trends for their

Table 2-5. Regression results of then (2) Service Providing sector for the 6-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable Effects of Fires on Employment (%)			
	All Fires	**Rural Fires**	**Urban Fires**	**Increasing Focal Counties**
Fire Happened	0.006**	0.008***	-0.005	-0.002
	(0.003)	(0.003)	(0.008)	(0.007)
1 Months After	0.004*	0.005*	-0.009	0.008
	(0.003)	(0.003)	(0.007)	(0.006)
2 Months After	0.004	0.005*	-0.006	0.004
	(0.003)	(0.003)	(0.007)	(0.006)
3 Months After	0.003	0.004	-0.004	-0.002
	(0.003)	(0.003)	(0.007)	(0.006)
4 Months After	0.003	0.002	-0.002	-0.0004
	(0.003)	(0.003)	(0.007)	(0.006)
5 Months After	-0.0002	-0.00005	0.001	-0.008
	(0.003)	(0.003)	(0.007)	(0.006)
6 Months After	-0.0005	-0.001	0.004	-0.003
	(0.003)	(0.003)	(0.007)	(0.006)
Observations	44,177	43,873	40,955	2,248
R^2	0.996	0.996	0.996	0.997
Adjusted R^2	0.996	0.996	0.996	0.997
Residual Std. Error	0.116 [df=43,856]	0.115 [df = 43,552]	0.117 [df=40,635]	0.095 [df=2,194]

respective counties, seven responses matched with trends we observed in the MTBS database and seven responses had a partial match (stating either increased frequency or burned area when we identified a trend for both). Only two participant responses mismatched observed trends, either citing opposite trends from our analysis or no stated observed changes in fire trends (despite being selected for interviews because of an increasing fire trend) when a significant trend is actually observed in the data. These mismatches may be due to differences in jurisdictional boundaries from our county-level unit analysis or the fact that MTBS data includes only fires larger than 400 ha.

Table 2-6. Regression results of the (1a) Good Producing: Natural Resource and Mining sector for the 6-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable			
	Effects of Fires on Employment (%)			
	All Fires	**Rural Fires**	**Urban Fires**	**Increasing Focal Counties**
Fire Happened	0.013*	0.014**	-0.004	0.092***
	(0.007)	(0.007)	(0.021)	(0.018)
1 Months After	-0.001	0.002	-0.009	-0.001
	(0.007)	(0.007)	(0.020)	(0.016)
2 Months After	-0.001	0.001	-0.009	0.015
	(0.007)	(0.008)	(0.020)	(0.016)
3 Months After	-0.002	-0.002	-0.013	0.009
	(0.007)	(0.008)	(0.020)	(0.017)
4 Months After	0.005	0.004	-0.022	0.019
	(0.007)	(0.008)	(0.020)	(0.017)
5 Months After	0.0003	0.001	-0.020	0.005
	(0.007)	(0.008)	(0.020)	(0.017)
6 Months After	-0.006	-0.004	-0.027	-0.028*
	(0.007)	(0.007)	(0.020)	(0.016)
Observations	39,406	39,112	36,346	2,181
R^2	0.953	0.954	0.953	0.949
Adjusted R^2	0.952	0.953	0.953	0.947
Residual Std. Error	0.306	0.304	0.305	0.254
	[df=39,094]	[df=38,800]	[df=36,035]	[df=2,128]

In general, most managers (14 participants) in the focused study areas said that changes in area burned and fire frequency influence decisions and adaptive practices in their jurisdictions, while four responded with 'No' and two with 'It Depends'.

> "Repeated large fires, in general, drives where to focus our mitigation and treatments as well as threatened communities/"

Adaptive strategies mentioned in response to changing fire trends are summarized in Table 2-8. Many managers mentioned increased efforts to reduce fuels and treat the landscape.

Table 2-7. Regression results of the (2a) Service Providing: Leisure and Hospitality sector for the 6-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable Effects of Fires on Employment (%)			
	All Fires	**Rural Fires**	**Urban Fires**	**Increasing Focal Counties**
Fire Happened	0.001	0.002	-0.017	-0.014
	(0.004)	(0.004)	(0.013)	(0.010)
1 Months After	0.005	0.005	-0.032***	0.010
	(0.004)	(0.004)	(0.012)	(0.008)
2 Months After	0.007	0.009*	-0.018	-0.003
	(0.005)	(0.005)	(0.012)	(0.009)
3 Months After	0.003	0.004	-0.011	-0.001
	(0.005)	(0.005)	(0.012)	(0.009)
4 Months After	0.001	0.001	-0.010	-0.006
	(0.005)	(0.005)	(0.012)	(0.009)
5 Months After	-0.0001	-0.001	0.001	-0.016*
	(0.005)	(0.005)	(0.012)	(0.009)
6 Months After	-0.001	-0.002	0.015	-0.005
	(0.004)	(0.004)	(0.012)	(0.008)
Observations	43,967	43,699	40,772	2,242
R^2	0.989	0.989	0.989	0.994
Adjusted R^2	0.989	0.989	0.988	0.994
Residual Std. Error	0.195	0.194	0.195	0.136
	[df=43,647]	[df=43,379]	[df=40,453]	[df=2,188]

"I think how we mitigate those fuels, where we do it and how we do it has changed quite a bit throughout the years. We're putting more emphasis on mitigation work to try to get ahead of that, so that we're not spending as much money and suppression to protect [values at risk]."

For decades, the predominant fire management paradigm in the U.S. prioritized fire suppression, with a more recent shift to longer-term planning on an ecosystem scale [25, 45]. Fire managers also mentioned repeatedly that large fires have driven policies that encourage them to more creatively minimize the size and frequency of fires. Some mentioned the need to shift firefighting tactics, including the assumption that fires will grow larger sooner.

> "The long history of fire suppression has affected the fire return interval on the landscape and built up fuel loads... There is an accelerated pace to try and treat more acres annually."

Managers who said fire trends did not influence their management decisions cited the limitations of overarching fire suppression protocols that superseded the ability to enact local adaptation strategies. Overall, 18 of the participants are implementing some sort of adaptation practice regardless of fire trends. These practices include prescribed burns, mechanical fuel treatments, habitat restoration, fuel treatment experimentation, interagency cooperation, and implementation of education and outreach programs. Managers emphasized the need for adaptation and mitigation work in order to control fuels, enhance suppression efforts, and restore habitat.

> "We're trying to solve the fire problem by or at the landscape health level, not just by the fire itself but with restoration because of all the invasives like cheat grass, etc. Because if you restore the landscape, then our fire frequency would go down."

While the majority of participants recognized changes in recent fire history, not everyone explicitly attributed these observed trends in fire to climate change. This result may be limited by the fact that they were not asked directly about this relationship during the interview – interviewers did not ask managers specifically if climate change influences fire frequency or area burned. Hence, opinions of climate change's influence on these trends is not known for all participants. Regardless, whether or not managers

Table 2-8. Adaptation strategies described by managers when asked how changes in area burned or fire frequency influenced their management decisions and adaptive practices.

Fire Trend Impacts to Adaptive Management	# of Managers
Informs/adjust fuels mitigation and calculations	8
Adjust fire response tactics	4
Affects treatments on the landscape	3
Experience informs management	3
Repeated large fires drives policy and management	3
Proactive management due to larger, frequent fires	3
Assume fires go larger sooner	2
Protect restoration investment	2
Alters grazing strategies	1

perceived increasing trends being caused by climate change, the efforts of most managers to implement adaptation practices is helpful for climate resiliency.

When asked if wildfire influenced economies in their area, 17 of the managers said ‘Yes’ while three were unsure. Some managers recognized the short-term positive impact that fires had on local economies, including the boost in goods and services when fire management teams patronized businesses near the fire. The influx of money and resources necessary to support a vast number of fire employees for days, weeks, or even months at a time was noticeable, especially in smaller, more rural communities. However, participants more commonly cited the negative and often longer-term impacts that fire has on communities, including the effects of smoke on health and tourism, closures to recreation areas and grazing allotments, loss of structures and property, the evacuation of residents, and the halt of commerce and e-commerce transportation with major road and highway shut-downs. While fire did increase the immediate opportunities for activities like salvage logging after the fire subsides, more often the negative long-term economic impacts for industries, such as sustainable timber harvesting, outweighed the short-term benefits. Managers spoke primarily about localized economic effects, but our economic analysis shows that some of these effects can be generalized to a broader region, even as broadly as the entire IMW. These generalizations are discussed later in this article.

Most managers (16 participants) said that the economic impacts of fire influenced their management decisions, while four were unsure.

> "As fire managers, [the economic impacts of fire] definitely does [influence decision-making]. And from the political aspect of it, the more you impact that economy, the more political pressure I think you're going to get to resolve that situation quicker."

Most managers claimed that they tried to minimize damages to life, property, and resources on the landscape as mandated by national policy. Managers that were unsure either could not elaborate or said it "depends on values at risk."

In light of the growing rural-urban divide in the IMW, the majority of managers (14 participants) cited differences in how they managed rural versus urban fires. Urban areas received the highest fire-fighting priority. Fires in rural areas allowed for more flexibility in management strategies, but were overall more complex in their approach due to a greater number of partnered agencies and public community involvement. A Fire Management Officer interviewed said:

> "[T]he difference between rural and urban definitely comes down to where the people are, the values at risk and what resources you have to work with. . . . and what makes it a higher priority is – it's a numbers game. More people, more structures, so it gains more [investment of resources]."

Respondents who said they do not manage rural vs. urban fires differently explained that the full suppression policy for their jurisdiction compels them to be aggressive in both settings, or that they base decisions on environmental factors or values at risk regardless of whether they occur in a rural or urban setting. Most managers spoke about the urgency and constraints of fighting fire according to mandated priorities of protecting life, property, and values at risk in populated areas and the WUI, while addressing the greater flexibility to allow fires to burn in rural areas.

When asked about the primary challenges to effectively mitigate wildfire risk, the top three categories participants mentioned were limited funding and resources, bureaucracy, and human behavior and education (Table 2-9). These three challenges were all sociological-based limitations, compared to the physically-based limitations, such as changing fuel loads and future climate, which ranked fourth and sixth most mentioned, respectively. Managers said that budget cuts, limited resources, and lack of personnel made it difficult to carry out mitigation projects or accomplish restoration goals. The U.S. Forest Service spends approximately 50% of its annual budget on fire suppression and estimates an increase to 67% of its annual budget (an increase to more than $1.8 billion) by 2025 [3]; however, the need for more funding to manage increasing fire on the landscape is stressing the already limited federal budgets. Bureaucratic challenges such as project delays, paperwork, conflicting conservation management goals, and pushback from constituents, created serious limitations when working with multiple agencies or stakeholders. Some managers call for change “where the policy that's being handed down and the budgets that are being handed down are coherent and they work together so that [fire managers] can do the work that [they] need to be doing.” Other participants said that educating and changing public perceptions about resource benefits from fires, and altering human behaviors, specifically reducing human ignitions, increasing awareness and "getting private land owners to accept the responsibility of the risk" while helping mitigate along the ever-growing urban growth boundary, were the greatest challenges for fire management.

> "Communities are encroaching on the National Forest. There's a lot of responsibilities that the landowners and the private landowners, private property owners, there's a lot of responsibilities that they have to accept on fire because of the location of their homes…that's the biggest thing that I've seen in the last 30 years is the occurrence of, the broadening of the Wildland Urban Interface, linear miles of it. It's increasing and that adds complexity along with the fuels that you have, and the weather that you have, the topography that you have, and adding the Urban Interface and those structures, that adds a lot of complexity."

Furthermore, while fuels mitigation was mentioned less than these socio-political challenges to adaptation, it was the most mentioned strategy impacted by fire trends (Table 8). This suggests that while managers acknowledge adapting fuels work to observed fire trends is an ongoing effort, such proactive measures can be constrained by the social and political challenges they face.

Table 2-9. Main challenges to wildfire risk mitigation identified by managers, summarized by categories and listed by the number of manager responses.

Identified Challenges to Management	# of Managers
Limited funding/resources	15
Bureaucracy	13
Human behavior/education	11
Changing fuel loads	7
Federal policy and administration shifts	5
Future climate	4
Competing interests/priorities	4
Development/growth	2

Participants in the three different geographic regions had different responses for some of the top cited categories. The majority of managers in Idaho had different responses compared to those in Utah and Arizona when it came to bureaucracy (ID = 10 participants; UT = 0 participants; AZ = 1 participants) and shifts in federal administration and policy (ID = 4 participants; UT = 0 participants ; AZ = 0 participants). While noting that the National Environmental Policy Act (NEPA) process is necessary for bureaucratic consent of all involved agencies, several Idaho participants mentioned it is difficult to accomplish projects in a timely manner. They further mentioned the difficulty and complexity of managing fire while also managing critical habitat and breeding area for the endangered Greater Sage Grouse (*Centrocercus urophasianus*). The conflicting management priorities of NEPA, Clean Air & Water Acts, and special threatened and endangered species regulations restrict the window and flexibility for managers to allow fires to burn on the landscape. It creates "a big, big task getting caught up on those acres" for treatment and mitigation. While managers in Idaho cited the greatest challenges with bureaucracy and shifts in federal administration and policy for their work, there may be geographic differences in the challenges that managers face elsewhere.

4. Discussion

We have three primary findings regarding fire and management strategies in the IMW. First, wildfire trends are increasing in area burned and fire frequency across the IMW at the regional scale, and for some counties and states. In the past 32 years, the IMW has experienced more frequent and larger rural fires, and more frequent urban fires (Table 2-2). However, this is not to say that all parts of the IMW are experiencing increasing fire trends. While we found significant trends at the regional level and for some states, there are clearly hotspots when looking at the county level. These hotspots are also not set over time, as counties that have not burned in our data time period may now have higher fuel loads. There are many potential reasons for increasing fire trends, including changing climate, changes in fire mitigation strategies, and changes in management priorities. Across the entire Western US, recent increases in wildfire are closely associated with increases in fuel aridity and is largely driven by anthropogenic climate change [46]. Our findings align with the argument that the predominantly dry IMW region is going to continue to be vulnerable due to high soil aridity [6, 7]. Increasing burned area could be further affected by shifts in management practices away from the immediate suppression of fire, particularly in rural areas. Alternative strategies include fuels reduction (e.g. prescribed fires, mechanical treatment) and use of fires for resource benefit (e.g. allowing fires to burn where values are not at risk).

Secondly, fires have had both positive and negative effects on employment rates at the county scale over the last 15 years. The timing and magnitude of these effects varied depending on economic sector. Generally, we observed short-term positive impacts of All Fires and Rural Fires across the IMW at the county level (See Table 2-3, Columns 1 & 2: All Fire & Rural Fire) immediately during and after a fire. These trends become weaker over time, but do not become negative. Participants referred to this as the short-term boom and long-term bust to local businesses and livelihoods, which is consistent with other research findings [23]. While we did see mostly short-term effects within the first 6 months after a fire, our study provides evidence of both short-term and long-term lagged effects with a few significant effects close to a year post-fire. When separating into the employment subsectors, fire had immediate positive impacts on the

(1) Goods Producing category. Fires can increase local investment through the construction of new buildings and the rebuilding of destroyed structures, roads and utility infrastructure [24]. These positive impacts are still present at the sub-sector level of (1a) Natural Resources and Mining. We are unable to fully account for this disconnect between immediate positive effects of fire and employment in the (1a) Natural Resources and Mining sub-sector. We expect that the full impacts of fires on this sector may be better quantified by more direct data, such as suppression costs, timber sale loss, and finer scale data, such as the census block level employment data. Unfortunately, such data were not available for this study. In the (2a) Leisure and Hospitality sector, there is a negative effect on employment during the month of the fire, which is consistent with previous studies [40]. Additionally, there are delayed positive impacts of all fires and rural fires across the IMW at the county level. The BLS defined the (2a) Leisure and Hospitality category as encompassing Arts, Entertainment & Recreation and Accommodation & Food Services, and these delayed positive impacts, especially in rural areas, could be driven by the return of tourism to an area after a 1-2 month period of official restrictions or visitation avoidance after a fire [22]. However, further analysis is needed to make this case, such as evaluating number of visitors to recreation areas. It should also be noted that there are other subsectors that may experience changes due to fire. Other studies were able to include additional subsectors of employment, such as construction and transportation, and found significant effects [41]. While we were able to find significance for the natural resource and leisure subsectors, we were unable to test effects for additional subsectors because there was insufficient data available for enough counties in other subsectors.

Third, most fire managers in the three areas in Idaho, Utah and Arizona acknowledged changing fire trends in their regions and are utilizing adaptive management strategies to mitigate changing fire patterns. They recognized some form of economic impact of fires and that these economic effects influence their management decisions. While we listed the number of participants who mentioned different topics to discuss the results of the interviews, we would like to emphasize that the more qualitative insights from the respondents should be the focus when analyzing the interviews. This third component contributes to the limited literature on understanding the decision-making process of fire managers and policy-makers [25]. The majority of managers interviewed feel the greatest challenges to fire adaptation are human factors, such as budget limitations, bureaucratic inefficiencies, and human decision-making, rather than environmental factors, such as climate change and accumulation of excessive fuel loads (Table 2-9). These human-related challenges are consistent with some of the wildfire risk literature, which calls for more landowner engagement in mitigation and adaptation [47]. Through these interviews, we also found connections to our fire trend analyses. Implementation of new fire mitigation techniques and improved firefighting efficiency, both of which are discussed in the interviews, may serve to counteract increases in area burned and/or fire frequency. For example, thinning, prescribed burning, and the creation of fire breaks have been implemented into many management plans to help reduce the size and severity of wildfires. There was some variance in the interviews, in terms of the adaptation strategies used by managers. This could be due to the differences in local context and the lack of larger-scale policies and alternatives for climate adaptation. While there was some variation, overall, there was general consensus in what influences managers' decisions and the challenges they face. These interviews provide in-depth insight to managers' perspectives in areas that have experienced increasing fire trends. However, they are limited in generalizability to the IMW. Future research on fire management, decision-making, and policy could contribute to the literature with studies with larger sample sizes across varying fire trend contexts.

The findings for the three sub-research questions of this study inform and support one another (Figure 1). Our study is the first to document a positive trend in area burned and fire frequency at multiple scales for the IMW region, and furthermore, to parse those trends into urban and rural settings, and explore the effects of those wildfire trends on local economies and adaptive management practices. Notably, we find that wildfire characteristics are increasing significantly but are spatially variable throughout the IMW. While fire managers in places experiencing increasing trends are generally aware of and adapting to those trends, many are experiencing limitations in adaptive capacity, which may become increasingly problematic in the predicted warmer and drier future in the IMW. Our qualitative interviews augmented our economic analysis as participants provided information regarding costs and risks for which quantitative economic data do not exist, including impacts on recreation and tourism. At the same time, the positive economic benefits observed several months after fires in our economic analysis (Table 2-4) were also captured in our qualitative interviews with managers who mentioned that burned areas can be logged for salvage timber. The economic analyses for the Increasing Focal Counties are in line with what managers said in interviews as well. For these focal counties, we find much larger negative impacts for (2a) Leisure and Hospitality than the other counties, indicating that more frequent or larger fires subsequently decrease tourism and recreation activity.

This study has been conducted based on available secondary data on fires and employment and the primary interview data we collected. Each dimension of the research had limitations that should be acknowledged. The fire trend analysis based on the MTBS dataset is limited to fires over 400 ha, thus overlooking smaller fires, which may be important, especially in urban settings. Economic data on fire suppression costs is not publicly available across the IMW study area, thus precluding a more direct analysis of fire-related economic impacts. Furthermore, our economic analysis of employment impacts of fire is limited to the last 15 years. Time and resource constraints limited the number of interviews with fire managers that could be conducted as well as the number of counties or areas that could be selected for this part of the investigation. Collectively, these data limitations inhibit generalization of findings across the study area and time period. Nevertheless, the insights provided here suggest trends and impacts related to fire are worthy of further investigation.

Our findings demonstrate that fires have significant economic impacts on affected communities, and that changing fire trends and economic effects influence the decision-making and planning of fire managers. The interdisciplinary nature of this research highlights the interconnectedness of the physical, economic, and social aspects of fire, and answers the call to utilize interdisciplinary approaches to address these complex social-environmental issues [48]. Our approach provides a novel and more holistic view of fire management that is often lacking. Lastly, our research contributes valuable insights into changing fire trends, the economic impacts of fire, and perspectives of fire managers in a rapidly changing landscape.

References

1. Westerling AL (2006) Warming and earlier spring increase Western U.S. forest wildfire activity. Science (80-) 313:940–943. https://doi.org/10.1126/science.1128834

2. Dennison PE, Brewer SC, Arnold JD, Moritz MA (2014) Large wildfire trends in the western United States, 1984-2011. Geophys Res Lett 41:2928–2933. https://doi.org/10.1002/2014GL061184.Received

3. USFS (2015) The rising cost of fire operations: effects on the Forest Service's non-fire work. United States Dep Agric For Serv 1–16

4. Knapp P (1998) Spatio-temporal patterns of large grassland fires in the Intermountain West, U.S.A. Glob Ecol Biogeogr Lett 7:259–272

5. Schoennagel T, Veblen TT, Romme WH (2004) The interaction of fire, fuels, and climate across Rocky Mountain Forests. Bioscience 54:661. https://doi.org/10.1641/0006-3568(2004)054[0661:TIOFFA]2.0.CO;2

6. Garfin G, Franco G, Blanco H, et al (2014) Chapter 20: Southwest. In: Melillo JM, Richmond TC, Yohe GW (eds) Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program, pp 462–486

7. Mote P, Snover AK, Capalbo S, et al (2014) Chapter 21: Northwest. In: Melillo JM, Richmond TC, Yohe GW (eds) Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program, pp 487–513

8. van Mantgem PJ, Nesmith JCB, Keifer M, et al (2013) Climatic stress increases forest fire severity across the western United States. Ecol Lett 16:1151–1156. https://doi.org/10.1111/ele.12151

9. Radeloff VC, Hammer RB, Stewart SI, et al (2005) The wildland-urban interface in the United States. Ecol Appl 15:799–805. https://doi.org/10.1890/04-1413

10. Theobald DM, Romme WH (2007) Expansion of the US wildland-urban interface. Landsc Urban Plan 83:340–354. https://doi.org/10.1016/j.landurbplan.2007.06.002

11. Hammer RB, Stewart SI, Radeloff VC (2009) Demographic trends, the wildland-

urban interface, and wildfire management. Soc Nat Resour 22:777–782. https://doi.org/10.1080/08941920802714042

12. Radeloff VC, Helmers DP, Kramer HA, et al (2018) Rapid growth of the US wildland-urban interface raises wildfire risk. Proc Natl Acad Sci 115:3314–3319. https://doi.org/10.1073/pnas.1718850115

13. United States Census Bureau (2018) Stats for stories: New Year's Day 2018. https://census.gov/newsroom/stories/2018/newyears2018.html

14. Stewart SI, Radeloff VC, Hammer RB, Hawbaker TJ (2007) Defining the wildland–urban interface. J For 201–207

15. Fitch RA, Kim YS, Waltz AEM, Crouse JE (2018) Changes in potential wildland fire suppression costs due to restoration treatments in Northern Arizona Ponderosa pine forests. For Policy Econ 87:101–114. https://doi.org/10.1016/j.forpol.2017.11.006

16. Calkin DE, Cohen JD, Finney MA, Thompson MP (2014) How risk management can prevent future wildfire disasters in the wildland-urban interface. Proc Natl Acad Sci 111:746–751. https://doi.org/10.1073/pnas.1315088111

17. Paveglio TB, Moseley C, Carroll MS, et al (2015) Categorizing the social context of the wildland urban interface: adaptive capacity for wildfire and community "archetypes." For Sci 61:298–310. https://doi.org/10.5849/forsci.14-036

18. Paveglio TB, Brenkert-Smith H, Hall T, Smith AMS (2015) Understanding social impact from wildfires: advancing means for assessment. Int J Wildl Fire 24:212–224. https://doi.org/10.1071/WF14091

19. McGranahan D (1999) Natural amenities drive rural population change. Washington DC

20. Paveglio TB, Carroll MS, Hall TE, Brenkert-Smith H (2015) "Put the wet stuff on the hot stuff": The legacy and drivers of conflict surrounding wildfire suppression. J Rural Stud 41:72–81. https://doi.org/10.1016/j.jrurstud.2015.07.006

21. Paveglio T, Edgeley C (2017) Community diversity and hazard events: understanding the evolution of local approaches to wildfire. Nat Hazards 87:1083–1108. https://doi.org/10.1007/s11069-017-2810-x

22. Dale L (2010) The true cost of wildfire in the western U.S . West For Leadersh Coalit 18

23. Nielsen-Pincus M, Moseley C, Gebert K (2013) The effects of large wildfires on employment and wage growth and volatility in the western United States. J For

111:404–411. https://doi.org/http://dx.doi.org/10.5849/jof.13-012

24. Lynch DL (2004) What do forest fires really cost? J For 102:42–49. https://doi.org/10.1093/jof/102.6.42

25. Dunn CJ, Calkin DE, Thompson MP (2017) Towards enhanced risk management: planning, decision making and monitoring of US wildfire response. Int J Wildl Fire 26:551–556. https://doi.org/10.1071/WF17089

26. Ager AA, Kline JD, Fischer AP (2015) Coupling the biophysical and social dimensions of wildfire risk to improve wildfire mitigation planning. Risk Anal 35:1393–1406. https://doi.org/10.1111/risa.12373

27. Thompson MP, Rodríguez Silva FY, Calkin DE, Hand MS (2017) A review of challenges to determining and demonstrating efficiency of large fire management. Int J Wildl Fire 26:562–573. https://doi.org/10.1071/WF16137

28. Calkin DE, Venn T, Wibbenmeyer M, Thompson MP (2013) Estimating US federal wildland fire managers? preferences toward competing strategic suppression objectives. Int J Wildl Fire 22:212. https://doi.org/10.1071/WF11075

29. Olson RL, Bengston DN, DeVaney LA, Thompson TAC (2015) Wildland fire management futures: insights from a foresight panel. Newtown Square, PA

30. Katuwal H, Dunn CJ, Calkin DE (2017) Characterising resource use and potential inefficiencies during large-fire suppression in the western US. Int J Wildl Fire 26:604. https://doi.org/10.1071/WF17054

31. Thompson MP, MacGregor DG, Calkin Thompson DE (2016) Risk management: core principles and practices, and their relevance to wildland fire. Fort Collins, CO

32. Daniel TC, Carroll MS, Moseley C (2007) People, fire, and forests: a synthesis of wildfire social science. Oregon State University Press, Corvallis, OR

33. Homer CG, Dewitz JA, Yang L, et al (2015) Completion of the 2011 National Land Cover Database for the conterminous United States-representing a decade of land cover change information. Photogramm Eng Remote Sensing 81:345–354. https://doi.org/10.14358/PERS.81.5.345

34. United States Census Bureau (2015) Cartographic boundary shapefiles. https://www.census.gov/geo/maps-data/data/tiger-cart-boundary.html

35. Eidenshink J, Schwind B, Brewer K, et al (2007) A project for monitoring trends in burn severity. Fire Ecol 3:3–21. https://doi.org/10.4996/fireecology.0301003

36. California Fire Alliance (2001) Characterizing the fire threat to wildland–urban interface areas in California. Methods 1–15

37. R Core Team (2016) R: a language and environment for statistical computing

38. Halpern CB, Lutz JA (2013) Canopy closure exerts weak controls on understory dynamics: a 30-year study of overstory–understory interactions. Ecol Monogr 83:221–237. https://doi.org/10.1890/12-1696.1

39. Bureau of Labor Statistics Quarterly census of employment and wages program. https://www.bls.gov/qcew/. Accessed 9 Apr 2018

40. Nielsen-Pincus M, Moseley C, Gebert K (2014) Job growth and loss across sectors and time in the western US: The impact of large wildfires. For Policy Econ 38:199–206. https://doi.org/10.1016/j.forpol.2013.08.010

41. Davis EJ, Moseley C, Nielsen-Pincus M, Jakes PJ (2014) The community economic impacts of large wildfires: a case study from Trinity County, California. Soc Nat Resour 27:983–993. https://doi.org/10.1080/08941920.2014.905812

42. Paveglio TB, Carroll MS, Jakes PJ, Prato T (2012) Exploring the social characteristics of adaptive capacity for wildfire: insights from Flathead County, Montana. Hum Ecol Rev 19:110–124

43. Boyatzis RE (1998) Transforming qualitative information: thematic analysis and code development. Sage Publications, Inc., Thousand Oaks CA, USA

44. Braun V, Clarke V (2006) Using thematic analysis in psychology. Qual Res Psychol 3:77–101. https://doi.org/10.1191/1478088706qp063oa

45. Ingalsbee T (2017) Whither the paradigm shift? Large wildland fires and the wildfire paradox offer opportunities for a new paradigm of ecological fire management. Int J Wildl Fire 26:557–561. https://doi.org/10.1071/WF17062

46. Abatzoglou JT, Williams AP (2016) Impact of anthropogenic climate change on wildfire across western US forests. Proc Natl Acad Sci 113:11770–11775. https://doi.org/10.1073/pnas.1607171113

47. Gan J, Jarrett A, Gaither CJ (2015) Landowner response to wildfire risk: adaptation, mitigation or doing nothing. J Environ Manage 159:186–191. https://doi.org/10.1016/j.jenvman.2015.06.014

48. Charnley S, Poe MR, Ager AA, et al (2015) A burning problem: social dynamics of disaster risk reduction through wildfire mitigation. Hum Organ 74:329–340. https://doi.org/10.17730/0018-7259-74.4.329

CHAPTER 3

AN INTIAL ANALYSIS OF WILDFIRE IMPACTS ON HYDROLOGIC REGIMES

Abstract

Large magnitude floods often follow wildfires due to changes in the physical landscape that affect rainfall-runoff processes. As wildfires become more frequent, the risk of high magnitude floods increases significantly. This study investigates rainfall-runoff ratios (i.e., the ratio of precipitation delivered to a watershed to the total discharge of stormflow measured at the mouth of the watershed) of nine river basins affected by wildfire. We use daily precipitation and flow data to compare pre and post wildfire runoff ratios. We use five metrics to analyze hydrologic change: 1) avg-avg, 2) avg-peak, 3) peak-peak, 4) variance, 5) recovery time. We use Random Forest to identify environmental variables that significantly influence changes in post-wildfire runoff ratios. Additionally, we run multilinear regression to further test the relationship between the identified environmental variables and changes in runoff. We observed increases in most metrics within all nine basins; the runoff ratio increased up to 880 percent. However, there are various approaches to measuring the change in runoff ratio and the percent increase depended on the metric used. No one metric accurately captured the hydrologic change in all nine basins, for example, some basins show a persistent shift in runoff ratio, while others only show a few floods with significantly different runoff ratios post-wildfire. The Random Forest analysis produced two significant models: peak-peak, with 50 percent variance explained, and avg-peak, with 42 percent variance explained. Both Random Forest models identified the area burned at high/moderate severity within the basin as an important explanatory variable. Additional variables consisted of geologic,

basin, and forest characteristics. The multilinear regressions produced a greater total percent variance explained for each of the two metrics, peak-peak producing 59 percent variance explained and avg-peak producing 75 percent variance explained. This disparity is likely due to Random Forest's tendency to overfit trends. Increased runoff after a wildfire increases flood risk, thereby affecting mitigation and restoration strategies and posing challenges for managers and landowners. Future analyses to understand relationships between environmental variables and changes in post-wildfire rainfall-runoff ratios would benefit from studying a larger number of burned areas across a more diverse set of landscapes.

1. Introduction

Climate change increasingly threatens both human and aquatic species in numerous ways, especially in areas that are already water-limited (Oki, 2006; Schlosser et al., 2014; Vörösmarty et al., 2010, 2000). Water-limited regions, such as the western US, are particularly vulnerable as climate change is expected to increase aridity, which in turn increases occurrence of wildfire (Bonfils et al., 2008; Hidalgo et al., 2009). Recent increases in aridity observed in the western US have already led to an earlier onset of spring and longer summers, thus increasing the wildfire season by 78 days since the mid-1980s (Westerling et al., 2006; Schoennagel et al., 2004).

As the western wildfire regime changes, it is important to understand the effects of wildfire on landscapes in water-limited regions. Wildfires significantly impact streamflow and are often followed by an increase in the magnitude and frequency of flooding events (Moody et al., 2013; Moody and Martin, 2001). Increases in streamflow due to wildfire over the past three decades already rival or exceed predicted near-term direct impacts of climate change in some areas of the western US (Wine et al., 2018). This level of impact is expected to expand into additional areas of the western US as wildfires continue to increase in size and frequency (Wine et al., 2018). Changes in hydrologic regimes affect both aquatic and human communities, and increasing vulnerability demands greater understanding of factors that impact streamflow following wildfire.

Wildfires initiate a cascade of hydrologic, geomorphic and ecological effects in watersheds. In particular, wildfires reduce rainfall interception and evapotranspiration, which leads to increases in the volume of water entering the river network. Under pre-fire conditions, interception rates in needleleaf forest across the western US can range from 21 to 24 percent (Link et al., 2004; Pypker et al., 2005). Reduced interception is especially prevalent in high severity burn areas, where interception declines to approximately zero and all incoming precipitation is available to generate runoff. Additionally, evapotranspiration is reduced to very low rates for several years following moderate to high severity wildfires, which eliminates a significant water efflux from the watershed and elevates soil moisture (Cardenas and Kanarek, 2014; Li and Lawrence, 2017). Wetter soils have lower infiltration capacity and therefore promote a higher amount of runoff (Cardenas and Kanarek, 2014).

Wildfires also substantially alter infiltration processes, leading to increased generation of surface overland flow, subsequently increasing surface erosion and sediment loading to streams by several orders of magnitude (Moody and Martin, 2001; Benavides-Solorio and MacDonald, 2005; Malmon et al., 2007; Robichaud and Brown, 1999). Hortonian overland flow occurs when rainfall intensity exceeds infiltration capacity such that excess rainfall is unable to infiltrate into the soil and thus runs off over the surface (Horton, 1945; Knighton, 1998). Under normal (pre-fire) conditions, infiltration capacity tends to decrease asymptotically during a storm event as a result of the increase in soil moisture, surface compaction by raindrops, translocation of silt and clay particles into pore spaces, and swelling of clay particles (Knighton, 1998). Wildfire exacerbates these effects by further increasing raindrop compaction, mobilizing significantly higher amounts of silt and clay particles that can clog soil pores, and by producing water-repellent ash, which seals the soil surface. The magnitude of these changes depends on various factors including soil type and the amount of bare soil exposed to rainfall post-wildfire (Mallik et al., 2016; Woods and Balfour, 2008). Soil water repellency, caused by the heating and distilling of hydrophobic organic matter which cools and condenses around soil particles, is influenced by cover density, species, soil texture, fire intensity and soil moisture. Several studies indicate that soil water repellency breaks down quickly after rain events, however, the strength and duration of repellency is not uniform throughout a burned area (Benavides-Solorio and MacDonald, 2001; DeBano, 1981; Huffman et al., 2001; Reneau et al., 2007; Stoof et al., 2010).

Developing a predictive understanding of how streamflow changes following wildfire is necessary to enable land managers to ensure the safety of downstream communities and enact effective and efficient restoration practices. New climate change models aimed at assessing water availability are just starting to incorporate the role of wildfires in hydrology. Model predictions of long-term annual water yields across the western US improve when wildfire characteristics are included in estimates of streamflow predictions (Wine et al., 2018). However, physical mechanisms underlying model results and the relative importance of specific environmental variables have yet to be determined.

Models used to predict site-specific increases in flood flows after a wildfire are heavily relied upon by land managers; however, they have a high degree of subjectivity, thus producing variable results with considerable uncertainty. The US Forest Service uses two approaches to analyze changes in peak flow, WILDCAT4 (Hawkins and Greenberg, 1990) and FIRE HYDRO (Cerrelli, 2005). Both models utilize a Curve Number (CN), which attempts to represent relationships between rainfall depth, runoff, and land-surface characteristics (e.g., soil type, land cover). Both models include metrics of precipitation, soils, vegetation, local treatment and conservation practices, hydrology, and topography to estimate runoff from watersheds. However each approach is subject to considerable limitations (USDA, 2013).

WILDCAT4 is a runoff/hydrograph model that uses triangular unit hydrographs to estimate peak flows (Hawkins and Greenberg, 1990; USDA, 2013). Model inputs include watershed slope, length of longest channel, area of Hydrologic Response Unit (HRU) (i.e., an area having a consistent hydrologic response), CN, storm duration, storm rainfall depth and storm distribution type. This model is only suitable for watersheds less than five square miles and the model user must specify the CN of pre- and post-fire conditions (Hawkins and Greenberg, 1990).

FIRE HYDRO analyses peak flows for defined time intervals of 2, 5, 10, 25, 50, and 100 year events (Cerrelli, 2005). FIREHYDRO model inputs include drainage area, slope, CN, and rainfall depth. This method is only equipped to model for 24-hour rainfall events. Similar to the WILDCAT4, the model user must choose the appropriate CN value.

The accuracy of both models' predictions is highly dependent on the CN, however no reliable method of choosing the CN value exists. Numerous guidelines have been suggested to aid modelers in choosing a correct CN for both models, however, differences among the guidelines, the subjectivity of choosing the CN, and a lack of data for calibration and validation necessarily yield predictions with high uncertainty (Cerrelli, 2005; Higgins and Jarnecke, 2007; Kuyumjian, n.d.; Livingston, Russell et al., 2005; Story, 2003; Stuart, 2000). For watersheds that contain heterogeneous soil types, land covers, and burn severities users calculate a weighted-average of all CNs to reduce computation complexity, however this can cause an underestimation of runoff; weighted-averages can under-predict runoff by 100 percent (Stuebe and Johnson, 1990; White, 1988). Underprediction is most apparent in watersheds that burn at both high and low severity, resulting in wide CN ranges (USDA, 2013). CN methods also have clear limitations in their applicability, such as storm duration and basin size, and it is widely acknowledged that post-fire peak flow models using CNs need further testing (Springer and Hawkins, 2005).

There is an increasing need for more accurate and accessible models predicting the change in the magnitude of runoff and peak flood events which leads to our primary research question: How well can we predict the magnitude of changes in rainfall-runoff ratios in wildfire-affected areas using readily available environmental metrics such as watershed area, burn area, and burn severity? The goal of this study is to evaluate the relationships between changes in runoff ratio and critical geologic, climatic, and fire characteristics in order to help increase the accuracy of predictive models. To attain this goal, we first identify numerous fires throughout the western US with sufficient data to support our analyses, and calculate the runoff ratio for pre- and post-wildfire rainfall storm events at each site. We then use Random Forest (RF) models to identify and analyze environmental variables that may influence changes in the runoff ratio, taking advantage of RF models' ability to handle complex, non-linear relationships (Cutler et al., 2007; Olson and Hawkins, 2012). We identify the readily available metrics that provide the most significant explanatory power using RF model variable importance measures. We then use partial dependence plots to determine the relationship between the change in runoff ratio and key predictor variables. To better understand the relationships between the significant RF model results and changes in runoff ratios, we run multilinear regression models between the significant response and predictor variables.

2. Methods

2.1 Site Selection

We first identify all fires spanning across the western United States (Arizona, California, Colorado, Idaho, Montana, New Mexico, Nevada, Oregon, Utah, Washington, and Wyoming) over a 30 year period (1986 – 2015). We use fire perimeter and burn severity data from the Monitoring Trends in Burn Severity (MTBS) dataset (www.mtbs.gov). MTBS provides fire size and burn severity data from all fires larger than 400 ha, though it has been criticized for overestimating burned area due to the inclusion of unburned patches within the fire perimeters (Abatzoglou and Kolden, 2013; Kolden et al., 2015, 2012). However, given the geographic extent and detailed information regarding burn severity MTBS is the most appropriate dataset for our analysis.

To winnow our analysis to fires in similar ecological settings, we use Level III Ecoregions, created by the US Geological Survey (USGS), to filter for mid- to high-elevation forested areas. Additionally, we filter the dataset according to the expected fire regime, sourced from LANDFIRE (www.landfire.gov). Fire regime describes vegetation characteristics and fire return intervals, classified by the historical average period between fires. We select for fires that consist of >50 percent of area corresponding to a 35-200 year return interval. Lastly, we filter for sites that have USGS gaging stations downstream that were operational before and after the fire occurred. This filtering process leaves us with seven qualifying fires: Salt Creek, UT 2002, Panic Rock, CO 2004, Missionary Ridge, CO 2002, West Fork Complex, CO 2013, Twitchell, UT 2010, Breckenridge Complex, CA 2011, and Borrego, NM 2002 (Fig. 3-1, Table 3-1).

2.2 Runoff Ratios

We used daily discharge and precipitation data to determine the runoff ratio for pre- and post-wildfire events. To calculate runoff ratio, we use the formula RR = Q/P where RR is runoff ratio, Q is equal to the volume of stormflow associated with the event (i.e., total discharge minus baseflow) and P is the volume of precipitation. We used daily discharge data from USGS gage stations to calculate discharge (Q) (https://waterdata.usgs.gov/nwis/sw). Daily precipitation data, sourced from the Parameter-elevation Regressions on Independent Slopes Model Climate Group (PRISM) (http://www.prism.oregonstate.edu/), is input into the ArcGIS Zonal Statistics as Table

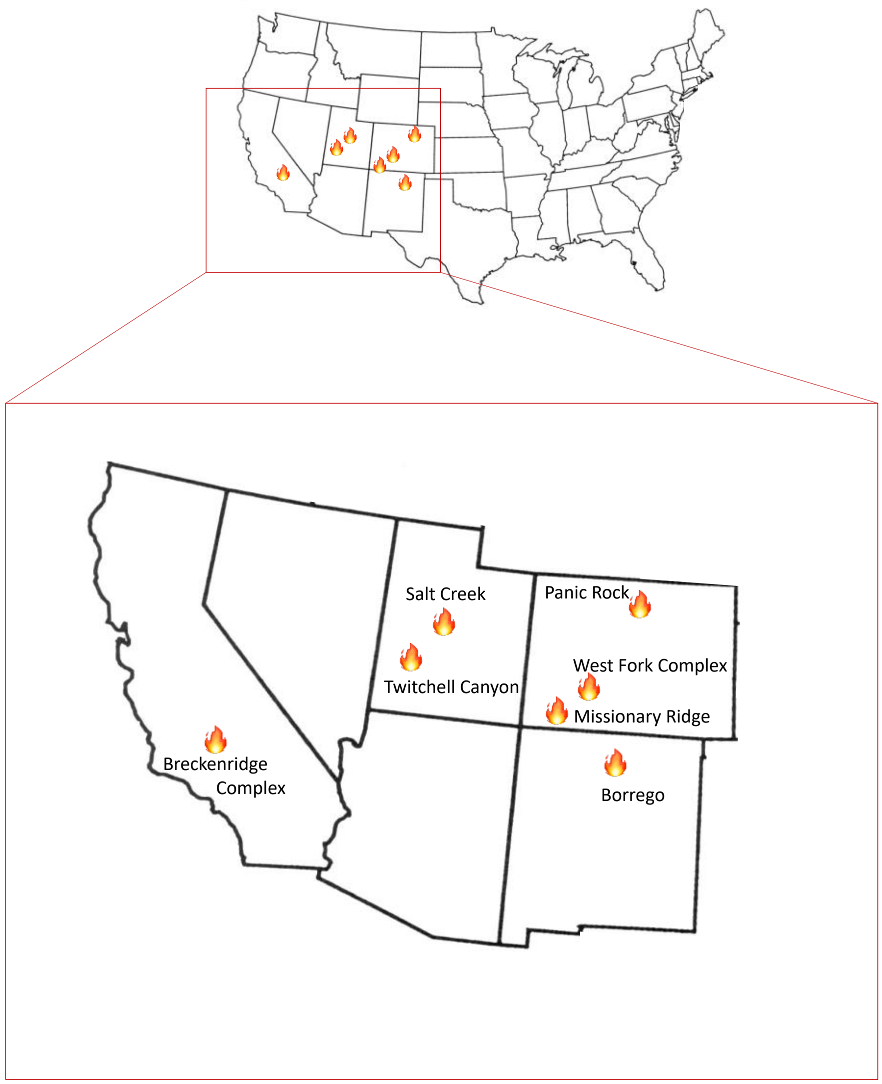

Fig. 3-1. Location map of the seven fires selected for hydrologic analysis. One watershed within each fire perimeter was selected for analysis with exception of West Fork Complex and Missionary Ridge, within each of which we selected two neighboring watersheds, yielding a total of nine analyzed watersheds.

Table 3-1
List of fires and selected associated data listed in order of increasing high to moderate severity burn area.

Fire Name	State	Size (acres)	USGS gage station	Fire year	Start year	End year	Watershed area burned (%)	High/moderate burn severity within basin (%)	Rock compressive strength (megaPascals)	Rock depth (cm)
Breckenridge Complex	CA	27231	11193020	2011	2006	2016	53	0	144	92
Panic Rock	CO	9013	6752000	2004	2000	2007	9	3	145	116
Borrego	NM	12877	8291000	2002	1999	2008	26	4	117	1145
Missionary Ridge	CO	68921	9363200	2002	1999	2010	15	7	88	109
West Fork Complex-South Fork	CO	34441	8219500	2013	2009	2017	12	9	72	129
Missionary Ridge 2	CO	68921	9353800	2002	2000	2010	27	16	55	122
Salt Creek	UT	26933	10146000	2007	2002	2017	25	18	70	114
Twitchell Canyon	UT	42951	10194200	2010	2005	2017	33	18	149	129
West Fork Complex-Goose Creek	CO	34441	8218500	2013	2008	2017	278	19	93	88

tool to calculate daily rainfall over the basin of interest. We only analyze storms occurring from July through October of each year to minimize the likelihood of including precipitation events primarily delivering snow, as well as rain-on-snow events that can release considerable amounts of water from the snowpack. Either of these situations lead to a calculation of runoff ratios that is not indicative of the event-scale rainfall-runoff processes that we aimed to quantify. Further, we select stormflow events that had a prominent peak that could be directly attributed to a measured precipitation event and exhibited a consistent baseflow at the start and end of the stormflow hydrograph.

We calculate daily stormflow for each selected stormflow event for five years before the fire and ten years after the fire. In a few cases, the length of analysis is limited by the available data. To calculate daily stormflow, we subtract baseflow, estimated as the amount of discharge immediately before and after the stormflow event, from the total daily measured streamflow. The runoff ratio is calculated by summing daily stormflow over the entire stormflow hydrograph and dividing by the total amount of precipitation associated with the event (Fig. 3-2).

There is no one widely accepted method used to calculate changes in runoff ratios (Dunkerley, 2012; Foufoula-Georgiou et al., 2016; Phillips et al., 2011; Schottler et al., 2014; Tedela et al., 2011). Different methods of calculation capture different hydrologic responses, each having unique impacts on the landscape. Therefore, we calculate five metrics (Fig. 3-3) to quantify how the runoff ratio changed as a result of a fire. The first metric compares the average pre-fire runoff ratio to the peak runoff ratio occurring within the first few years following the fire (avg – peak). This allow us to see how peak floods

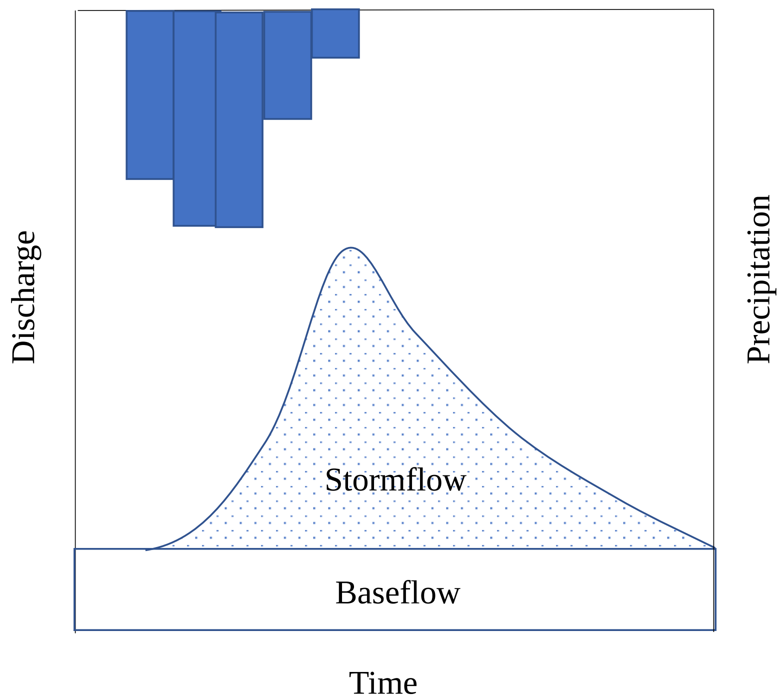

Fig. 3-2. Conceptual discharge and precipitation hydrograph. The hydrograph is separated into the stormflow component, spotted blue, and baseflow component, solid transparent blue. Precipitation rate is shown in solid dark blue.

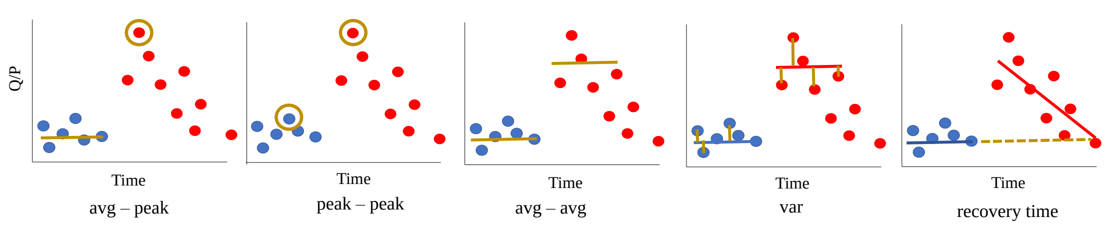

Fig. 3-3. A conceptual model of the five approaches to calculating changes in runoff ratios. Blue dots represent pre-fire data, while red dots indicate post-fire data. Gold symbols show the variables being compared. Hollow gold circles indicate peak magnitudes being compared. Horizontal solid gold lines represent the average of points. Vertical solid lines represent the variance. The dashed horizontal line represents time. The gold shaded region represent the time of interest for each analysis.

increase and analyze variables impacting increased magnitude flows compared to pre-fire conditions, while partially controlling for any anomalous high and low flows occurring pre-fire. The second metric compares peak runoff ratios measured pre- and post-fire (peak – peak). This compares the difference between the highest flood magnitudes pre- and post-fire conditions, thus examining the differences between extreme events. The third metric compares the three-year average pre-fire runoff ratio to the three-year average post-fire runoff ratio (avg – avg) to determine if there is a persistent short-term increase in flood events after wildfires. The fourth metric quantifies the three-year variance of runoff ratios pre- and post-fire (var). Examining changes in variance may lead to a better understanding of whether areas are vulnerable to extreme changes in flood regime, capturing both drought and substantial increases in flow. Lastly, the fifth metric calculates the amount of time it takes for the linear trend of the post-fire data to return to the average pre-fire runoff ratio value (recovery time). If the avg – avg metric indicates a decrease in pre- and post-fire runoff, the recovery time is considered to be zero. Recovery time is important because if long-term changes in flood persist, it is important to understand where they occur and why they continue.

2.3 Random forest and multilinear regression analysis

We use RF models to analyze the complex relationships between environmental metrics (predictor variables), such as burn severity, and our five metrics that quantify changes in runoff ratio (response variables). RF models are an ensemble-tree based statistical tool that builds on Classification and Regression Tree (CART) algorithms. The CART algorithm iteratively partitions data into a set of regular areas so that similar response values are grouped until maximum homogeneity within the groups is achieved

(Strobl et al., 2009). This study focuses on regression models, thus homogeneity is measured by the mean squared error (%MSE). RF models expand this method as they train each tree based on a bootstrapped sample of the dataset. RF models incorporate variable selection within each stage of partitioning; only a random subset of variables are considered at each node split (Strobl et al., 2009). When the tree achieves homogeneity, predictions are made onto the samples and averaged across the entire set of trees. However, these predictions are not projected onto the bootstrapped samples, called out-of-bag samples. Out-of-bag samples act to cross-validate the accuracy of estimates because predictions made onto the out-of-bag samples are not used to train the models (Cutler et al., 2007). The randomness imposed by bootstrapping and the process of weeding out unimportant predictor variables ensures that individual trees are independent (Breiman, 2001; Cutler et al., 2007).

RF models have been shown to perform as well as, or better than, alternative classification and regression methods in ecological studies and have many advantages compared to alternative methods (Cutler et al., 2007; Olson and Hawkins, 2012). First, they do not require distributional assumptions of variables as they are fully non-parametric (Cutler et al., 2007; Olson and Hawkins, 2012). Second, RF models have the ability to perform single or multiple linear regressions and capture non-linear interactions among predictor variables, which is advantageous to this study as hydrologic impacts of wildfire during post-wildfire hydrologic recovery are often non-linear (Wine et al., 2018). Third, RF models are applicable for datasets with a small number of observations (n) and a large number of variables (p) (Cutler et al., 2007; Strobl et al., 2009). Because the predictor variables considered at each node split are limited to a random subset of the entire set of predictor variables and the average of an ensemble of trees is used to measure variable importance, RF models are able to detect important relationships in small 'n' datasets that would be missed using alternative methods (Strobl et al., 2009). This is particularly beneficial for this study as we have a limited number of observations (n = 9). Lastly, RF results are used to interpret relationships within multivariate datasets through the use of variable importance and partial dependence plots which allows us to understand the relationship of variables with the highest explanatory power for predicting changes in runoff ratio metrics.

We construct separate RF models for each of the five measures of runoff ratio changes described above: 1) avg – peak 2) peak – peak 3) avg – avg 4) var 5) recovery time. We build 500 trees for each model run because model performance did not improve with higher numbers of trees. To find the values for the size of the set of predictor variables available at each partition, we use p/3 where p is the total number of predictor variables in the model.

We use variable importance plots, generated from RF models, to identify unimportant variables. We eliminate unimportant variables using an iterative modeling approach thereby sequentially eliminating the least important variables from each model, continuing until model performance declined (Olson and Hawkins, 2012). This process allows us to create a model that provides the greatest amount of accuracy. We use the out-of-bag %MSE to determine model accuracy. Lastly, we create partial dependence plots for each significant predictor variable to assess the relationship between runoff and the significant predictor variables.

Data within our RF models contains variables extracted from StreamCat (https://www.epa.gov/national-aquatic-resource-surveys/streamcat), which includes watershed characteristics such as vegetation and geologic variables. We use MTBS data to calculate fire characteristics for each fire, such as percentage upstream burned at high severity, percentage upstream burned at high/moderate severity, and percentage of watershed burned (Table 1). The StreamCat and fire characteristic variables provide 64 total environmental model inputs. We run a correlation test in R Programming, using the package Corrplot (https://cran.r-project.org/web/packages/corrplot/corrplot.pdf), to determine if there is a high correlation between these input variables ($r > 0.8$). We eliminate the highly correlated inputs as they might interfere with RF's ability to accurately determine the greatest explanatory variables, leaving 43 variables. To determine if the correlated variables impact the RF model results, we also run the RF models for each of the five metrics using complete 64 variable dataset.

We run multilinear regressions on significant runoff ratio change metrics using the top predictor variables determined by the RF model. If the RF model does not provide significant results, we do not complete a multilinear regression for that model. We use the built-in R function 'lm' to complete the multilinear regressions (https://www.rdocumentation.org/packages/stats/versions/3.6.0/topics/lm). The lm function performs linear regressions, single stratum analysis of variance, and analyzes covariance. In these models, we use the dependent variable (Y), the runoff ratio metric, and the significant predictor variables ($X_1+\ldots+X_n$), where n is the number of significant predictor variables, to better understand how changes in runoff ratio correlate linearly with predictor variables. We use performance measures, such as residual standard error and R-squared values to evaluate the variance explained by the model and model accuracy.

3. Results

We find that the runoff ratio increases after a fire in nearly all cases (Fig. 3-4, Table 3-2). However, the magnitude of change in runoff ratio differs between each of the five metrics (Table 3-2). Consistent with past work, we have found that fire, forest, and geologic characteristics affect changes in runoff ratio post-wildfire.

The greatest increase in peak – peak occurred in West Fork Complex- South Fork with a 190 percent increase (Table 3-2). All sites increased in peak flooding after wildfires, with the exception of Breckenridge Complex, which did not change. The RF results for the peak – peak runoff ratio indicate that percent burned at high to moderate severity and rock compressive strength explain 50 percent of the total variance (Fig. 3-5). The RF model provided consistent results for both the uncorrelated and complete datasets. Rock compressive strength and peak – peak runoff are positively correlated, while percent of watershed burned at high to moderate severity are negatively correlated (Fig. 3-6). The multilinear regression explained 59 percent of the total variance ($p < 0.2$). Additionally, a linear regression between peak – peak runoff and area burned at high to moderate severity explained 75 percent of the total variance ($p < 0.001$, Fig. 3-7).

Comparison of the pre-fire average runoff ratio to the post-fire peak runoff ratio (avg – peak) produced the largest change in runoff ratio at nearly all of the sites (Table 3-2). The avg-peak change was greatest in Salt Creek which increased 880 percent. The two lowest severity fires, Panic Rock and Breckenridge Complex, increased the least at 90 and 117 percent.

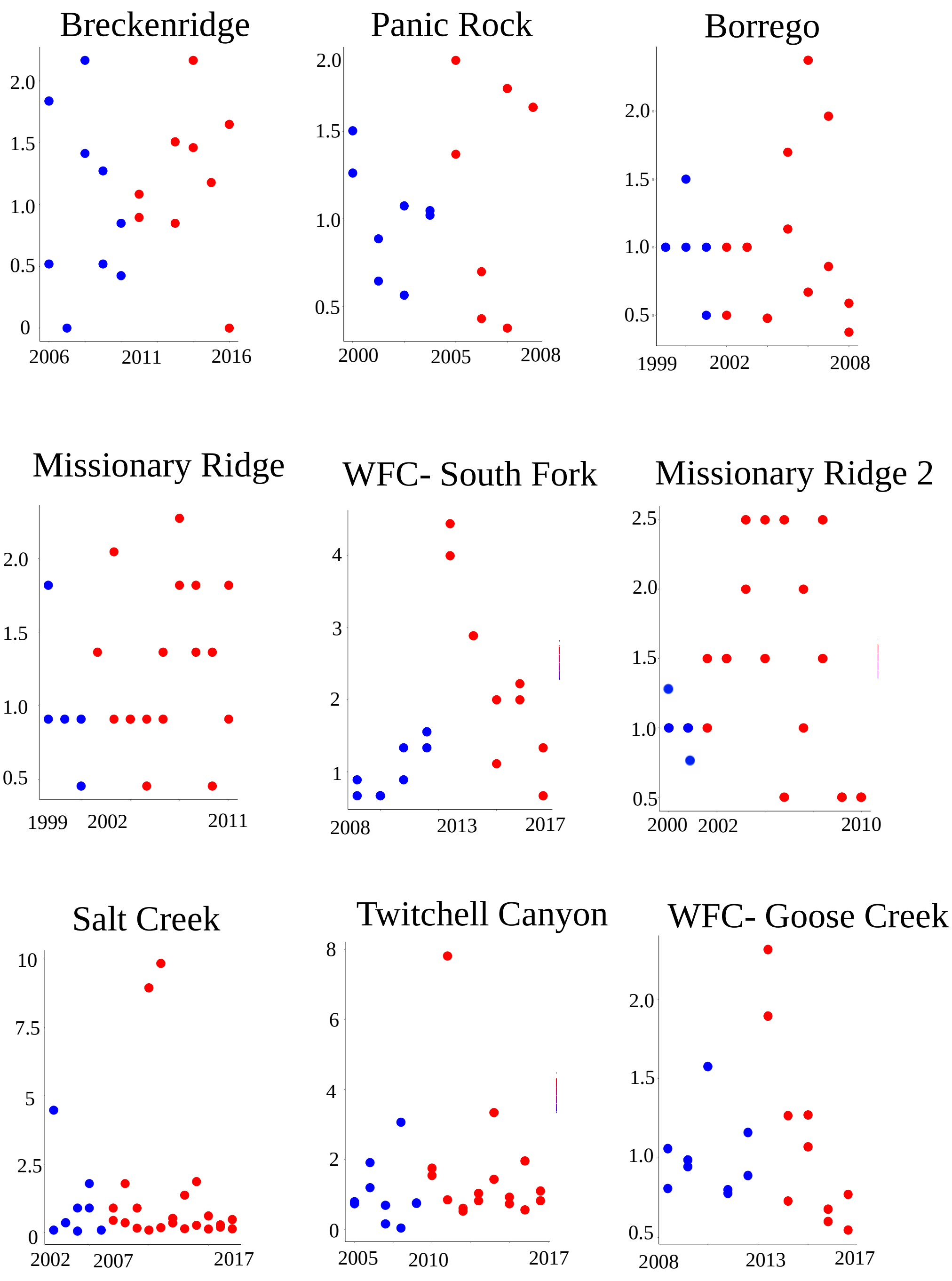

Fig. 3-4. Runoff ratio graphs for each analyzed fire. Pre-fire runoff ratios are shown in blue, while post-fire runoff ratios are shown in red. Three years are shown along the x-axis, representing the start year of the study, the year the fire took place, and the end year of the analysis. The points have been normalized by the average of the pre-fire runoff ratios. The fires are ordered by increasing high/moderate severity burn area within the watershed.

Table 3-2
Runoff ratio changes for the nine analyzed basins listed in increasing order of high/moderate burn severity. All analyses are represented in percent increase, except for recovery time which is represented in years.

Fire name	avg - peak	avg - avg	peak - peak	var	recovery time
Breckenridge Complex	117	-2	0	-80	0
Panic Rock	90	20	30	850	5
Borrego	140	-30	60	-20	7
Missionary Ridge	130	20	30	0	6
West Fork Complex- South Fork	340	170	190	1150	6
Missionary Ridge 2	150	240	150	150	5
Salt Creek	880	2	120	-30	11
Twitchell Canyon	680	140	160	550	5
West Fork Complex- Goose Creek	130	40	140	210	5

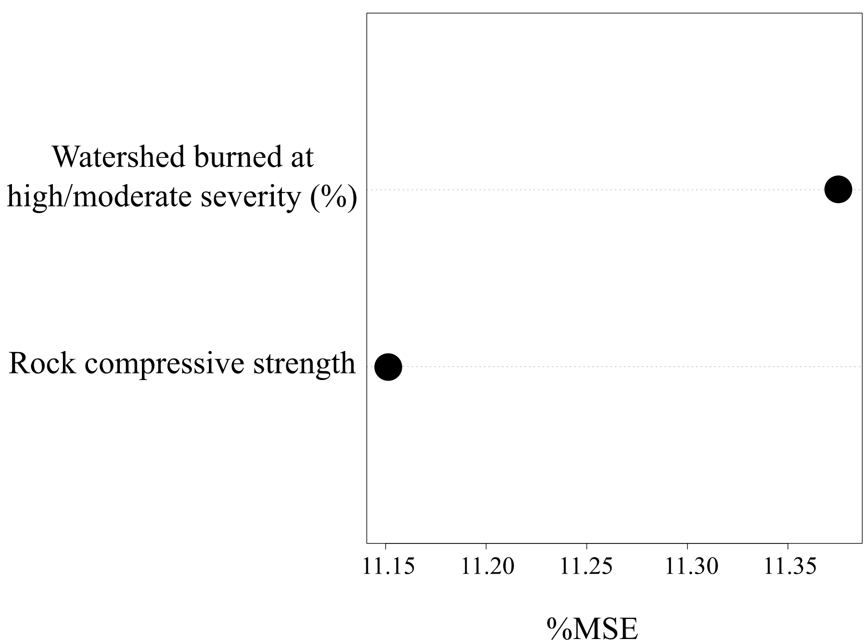

Fig. 3-5. The RF variable importance plot for peak – peak showing percent mean standard error (%MSE) for the most significant predictor variables.

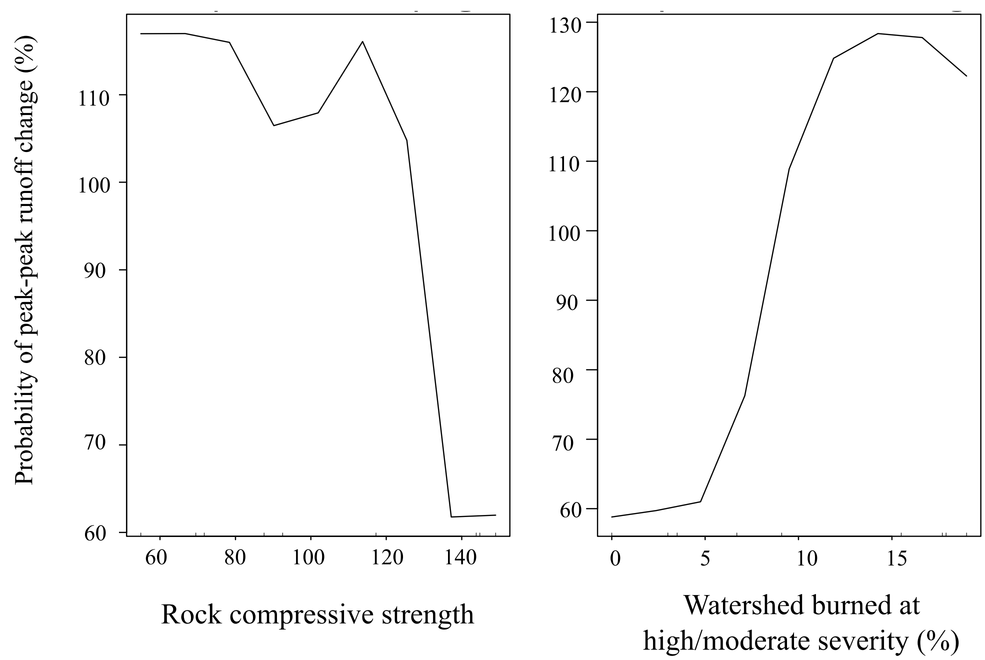

Fig. 3-6. Partial dependence plots showing the top predictor variables indicated as the most important by the RF model for the peak – peak runoff ratio metric. The tick marks on the inside of the plot on the bottom represent 10 % increments of data spread.

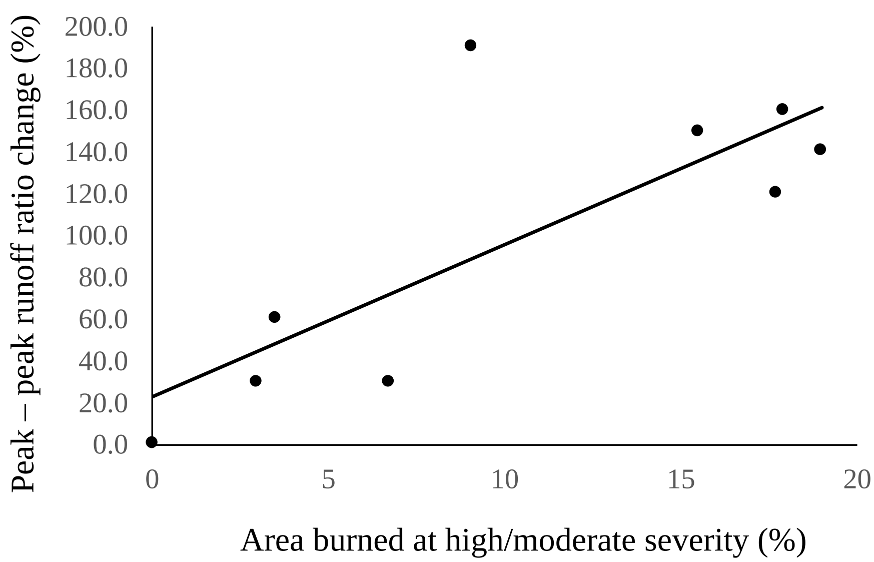

Fig. 3-7. Peak – peak analysis and area burned at high to moderate severity have a significant linear relationship ($R^2 = 0.75$, $p < 0.01$).

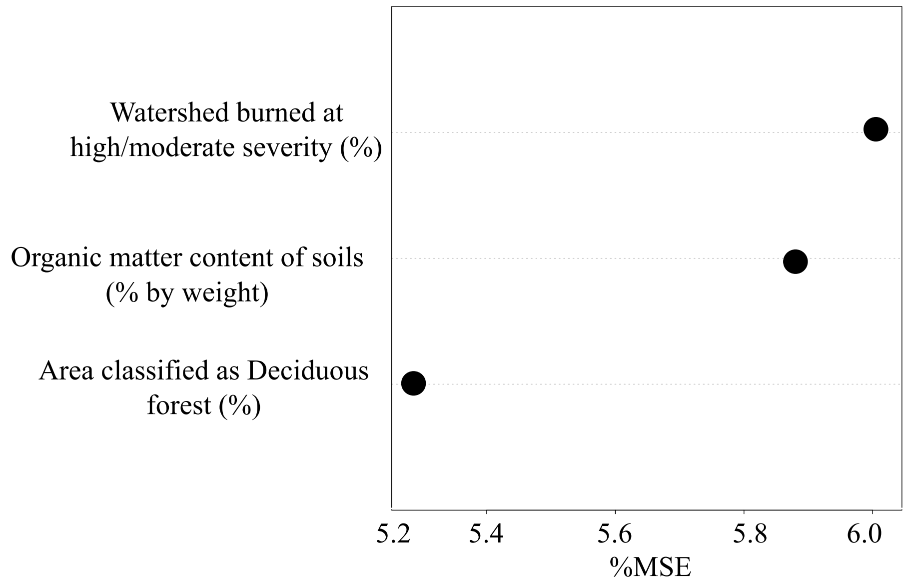

Fig. 3-8. The RF variable importance plot for avg – peak using the uncorrelated variables dataset show the highest explanatory variables in mean standard error (%MSE).

The avg – peak RF model results differed between the uncorrelated and complete dataset. The uncorrelated dataset results showed that the percent area of watershed burned at high to moderate severity, mean organic matter content (% by weight) of soils and percent area that is deciduous forest explained approximately 42 percent of the total variance (Fig.3- 8). The avg – peak runoff ratio change is positively correlated with all three of these variables (Fig. 3-9). The multilinear regression model for avg – peak runoff ratio change as a function of these three predictor variables produced an R^2 value of 0.75 (p-value < 0.1). Additionally, a linear regression between avg – peak runoff ratio and area burned at high to moderate severity explained 54 percent of the total variance (Fig. 3-10).

The avg – peak RF model run on the complete dataset results indicated that the percent area of watershed burned at high to moderate severity, watershed area and rock depth (mean depth to bedrock of soils) are the most significant predictor variables, but only explain approximately 18 percent of the variance according to the RF analysis (Fig.

3-11). The avg – peak runoff ratio change is positively correlated with percent watershed area burned at high to moderate severity and rock depth. Avg – peak runoff ratio change is negatively correlated with watershed area (Fig. 3-12). The multilinear regression model using the variables produced by the complete variable avg – peak RF model generated greater explanatory power with an R^2 value of 0.57 (p-value < 0.21).

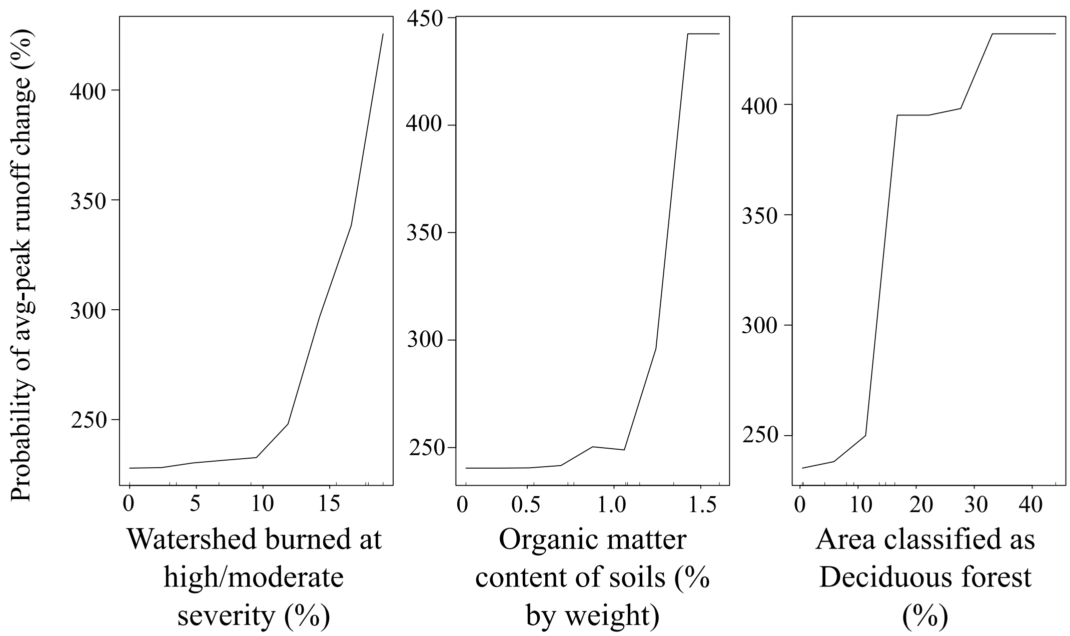

Fig. 3-9. Partial dependence plots show the predicted value of the magnitude of change of runoff ratio given the percentage of watershed burned at high to moderate severity, organic matter content of soils and area classified as Deciduous forest as a result of the RF avg – peak uncorrelated dataset analysis.

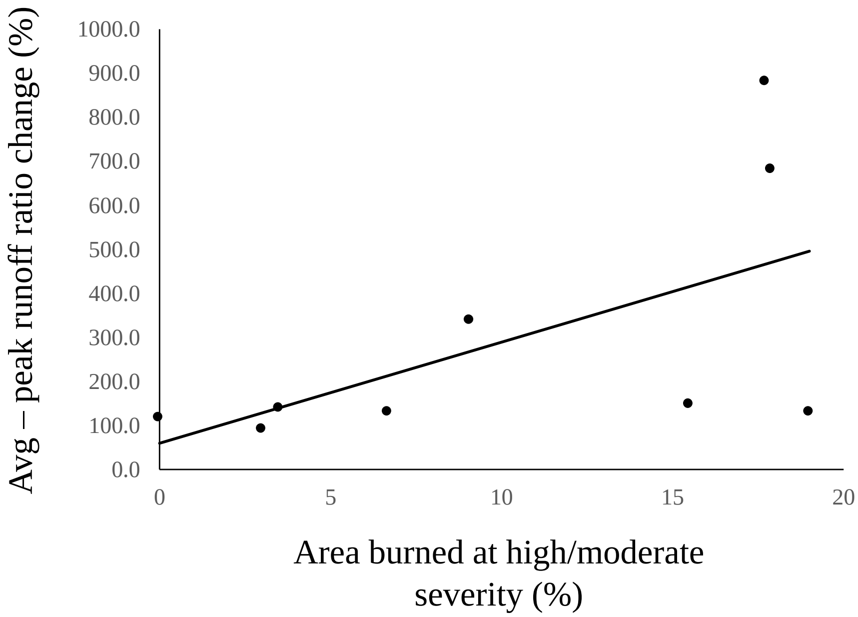

Fig. 3-10. The linear relationship between avg – peak runoff ratio change and area burned at high to moderate severity ($R^2 = 0.51$, $p < 0.1$).

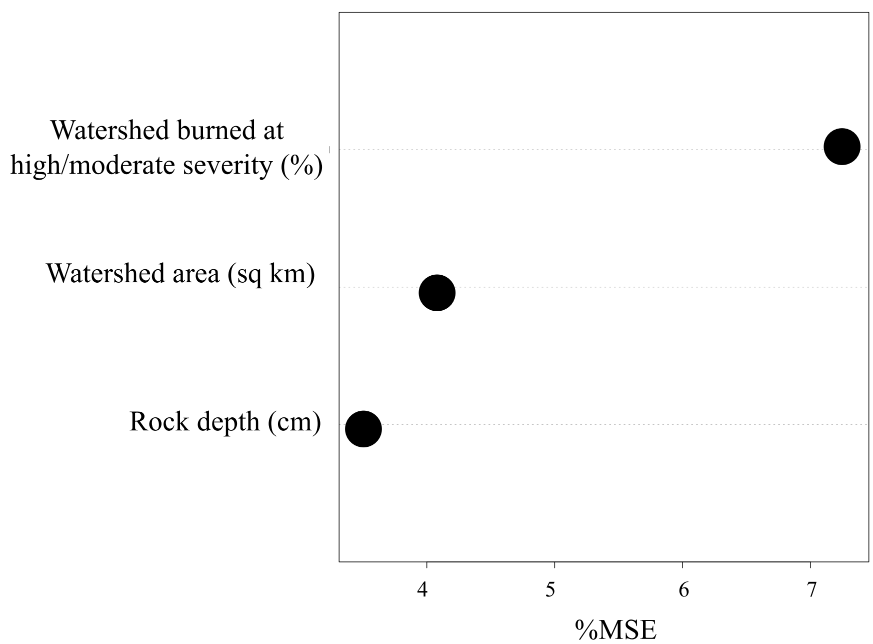

Fig. 3-11 The RF variable importance plot for avg – peak using the complete dataset showing the highest explanatory variables in mean standard error (%MSE).

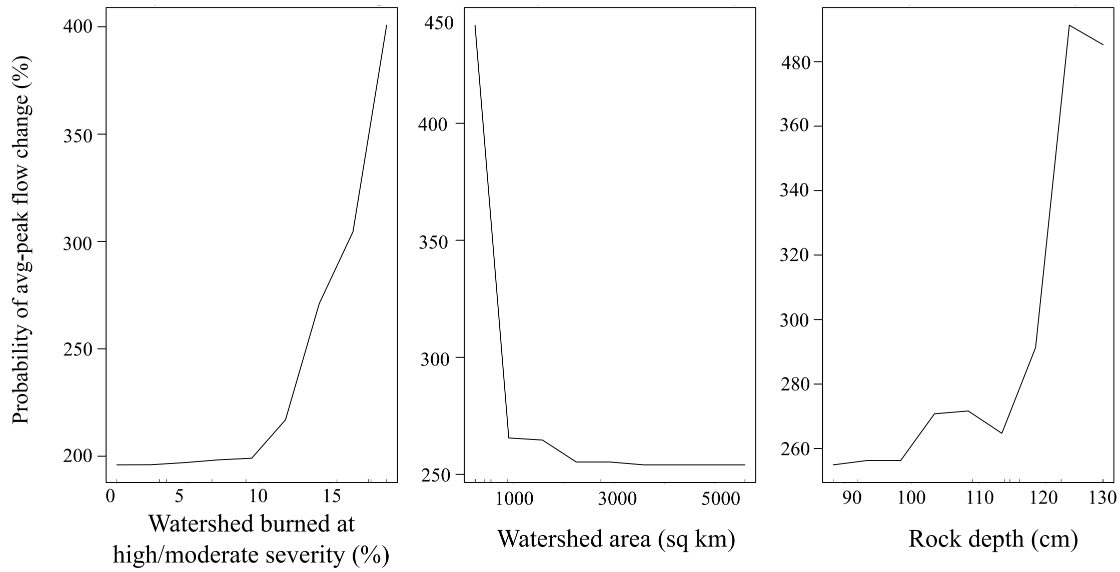

Fig. 3-12. Partial dependence plots show the predicted value of the magnitude of change of runoff ratio given the percentage of watershed burned at high/moderate severity, watershed area and rock depth as a result of the RF avg – peak complete dataset analysis.

Comparison of the pre-fire average runoff ratio to post-fire average runoff ratio (avg – avg) showed variable results between the fires. Most sites increased in avg – avg runoff ratio change except Breckenridge Complex which decreased by three percent, and Borrego which decreased by 30%; however these decreases may not be significant. The largest increase was Missionary Ridge 2, of 240 percent. West Fork Complex- South Fork and Twitchell Canyon also both increased over 100 percent. The RF model did not produce significant predictor variables with high explanatory value for the avg-avg response variable using either the uncorrelated or complete dataset.

Analysis of the change in variance (var) showed differing results among sites (Table 2). Specifically, the variance in runoff ratio did not change at Missionary Ridge 1, whereas Breckenridge, Borrego, and Salt Creek decreased in variance and the remaining sites increased in runoff ratio variance post-wildfire. The RF model did not provide significant results between variance and important predictor variables using either the uncorrelated or complete dataset.

Recovery time varied considerably between each fire ranging from zero to 11 years (Table 3-2). The longest recovery time was Salt Creek, however this may be driven by high outliers in peak flow. Most of the other fires took five to six years to recover to average pre-fire conditions, with the exception of Breckenridge which did not require any recovery time. The RF model was not able to parse out significant relationships between recovery time and important predictor variables using either the uncorrelated or complete dataset.

4. Discussion

There is no singular comprehensive way to analyze runoff ratio change, and only selecting one metric to analyze a basin may result in hydrologic responses being overestimated, underestimated or missed completely. Using the five metrics allowed us to explore various ways that runoff ratio characteristics change after wildfire, such as short spikes in runoff ratio increases or more prolonged increases. The magnitude of change in runoff ratio differs considerably between site locations. The greatest increase in avg – peak analysis was at Salt Creek, however, the greatest increase in the peak – peak occurs at West Fork Complex- South Fork. Additionally, sites did not increase or decrease uniformly across the five metrics. For example, results from the five metrics describe no change, increase and decrease in runoff ratio, depending on which metric is analyzed, for the Breckenridge Complex fire. The avg – peak analysis indicates that runoff will increase over 100 percent, however there is negligible decrease in avg – avg and there is zero change in peak – peak runoff ratios. This is explained as there was a high degree of variability in runoff ratios pre-fire, so while the post-fire peaks compared to pre-fire average may seem large, there is no change in extreme peaks or pre- and post-averages. These results demonstrate there are multiple ways runoff can change, and multiple metrics are needed to assess changes.

Significant RF model results for avg – peak uncorrelated variables, avg – peak correlated variables, and peak – peak highlight the importance that fire specific characteristics have on runoff ratios. All significant RF models dictate that area burned at high to moderate severity is one of the strongest explanatory predictor variables. This result is consistent with past work concluding that runoff ratio change increases as percent watershed area burned at high or moderate severity increases (Benavides-Solorio and MacDonald, 2001; Mallik et al., 2016; Moody and Martin, 2001; Stoof et al., 2010; Woods and Balfour, 2008). When we compare the runoff ratio graphs for low severity fires and high severity fires, there are distinct differences in the patterns of response (Fig. 3-13). The Breckenridge complex fire burned at zero percent high or moderate severity (Table 3-1), and we see little change in runoff ratio following that fire (Fig. 3-9). The Salt Creek basin of the Westfork complex fire burned at ~18 percent high to moderate severity (Table 3-1) and post-fire we see that the avg – peak increased approximately 880 percent (Fig. 3-11). West Fork Complex- South Fork, which burned at 11.5 percent high to moderate severity, increased 190 percent in the peak- peak metric. Although these areas are not the highest burn severity fires, they are both within eight percent of the same area burned at high to moderate severity. Additionally, the West Fork Complex- Goose Creek, the highest severity fire, also increased over 100 percent in both avg – peak

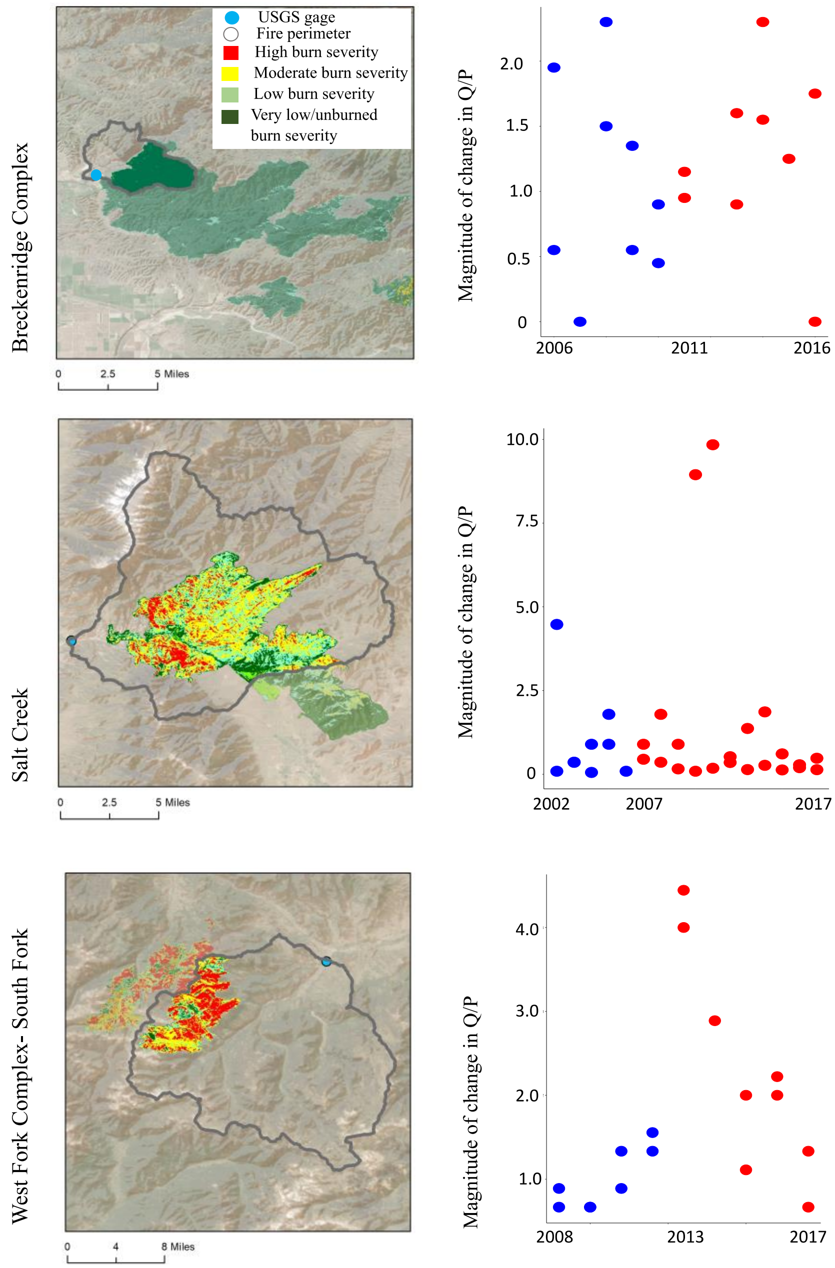

Fig. 3-13. The burn severity maps and associated avg – peak runoff ratio plot for Breckenridge Complex (little to no change between pre- and post-fire) and Salt Creek (largest increase in avg – peak metric) and West Fork Complex- South Fork (largest increase in peak – peak metric). Below, pre-fire stormflow ratios in blue and post-fires stormflow in red. The runoff ratio has been normalized by the average pre-fire stormflow; therefore, the normalized magnitude of change in runoff ratios are on the y-axis.

and peak – peak metrics. It is clear that in areas with higher severity fire, there are more substantial increases in runoff ratios.

RF model results also indicate the importance of geologic composition. Both rock depth and rock compressive strength appear as important variables. One hypothesis of why rock depth and rock compressive strength positively correlate with increases in runoff ratio is their effect on porosity and infiltration rates. Greater runoff is expected in areas with shallow soils and exposed bedrock due to limited porosity and infiltration. Changes in runoff are more likely to occur in areas where significant changes to the soils occur. Therefore, the importance of rock depth and compressive strength may reflect hillslope porosity and infiltration. Different geologic metrics should be tested to see if stronger relationships develop.

Uncorrelated variables avg – peak RF model results indicated the importance of organic matter and forest type. We hypothesize that the organic matter and vegetation type are related to changes in runoff ratio as they impact the magnitude and duration of soil hydrophobicity. As predicted by our model, greater organic matter content correlates with larger increases in runoff. Additionally, as vegetation burns, erodibility increases leading to greater runoff. These results should be tested against more forest types to better understand the importance these variables have on runoff.

Although the RF model results illustrate important relationships between physical variables and changes in runoff ratios, we expected additional variables to have higher explanatory power. These include slope, a metric of precipitation and erodibility (k-factor). Slope is important to runoff ratio as steeper areas are subject to higher velocity water runoff, and therefore increased shear stress and diminished time to allow water to infiltrate into the soils. However, neither percent > 10% steepness, nor percent > 20% steepness proved to be strong predictor variables. This may be because this study focused on mid-high elevation forested areas and, therefore, all areas studied are considerably steep. The importance of slope might change significantly if future studies compare fires in different ecoregions and regimes with shallower slopes.

Precipitation was expected to be a key explanatory variable because with greater precipitation intensity, duration, and initial moisture content, the amounts of overland flow and flooding also increase. Like slope, our sites may be too similar in annual precipitation for RF models to differentiate precipitation as a strong predictor variable. Precipitation metrics may provide further insight into changes in post-fire runoff. However, more research should be done to further test the strength of their impact.

Erodibility is important as it represents the susceptibility of soil to erode and therefore impacts the rate of runoff (Renard et al., 2000). As vegetation burns, soil water repellency increases and root stability decreases, we expect the erodibility to increase, leading to an increase in runoff. Our K values differ between basins; however, they might not differ enough to be detected as a significant predictor variable. Further analysis should be done on a more diverse set of watersheds to examine if erodibility impacts runoff as initially expected.

The RF models and multilinear regression models provide different levels of significance between runoff and important predictor variables. RF models consistently produce more conservative results thereby possibly understating of the explanatory power of the predictor variables. The avg – peak uncorrelated variable data set RF model explains approximately 42 percent of the total variance while the multilinear regression model explains approximately 57 percent of the total variance. Additionally, multiple linear regression explaining 51 percent of the total variance ($p < 0.1$) between avg – peak runoff ratio and percent of watershed burned at high or moderate severity, as compared to 42 percent of variance explained with the RF model. The linear regression between avg – peak and area burned at high to moderate severity indicates more variance with increasing burn severity. This is expected because additional variables start to increasingly influence changes in runoff in higher severity areas. For example, in a low severity area, there may still be vegetation present and therefore rates of evapotranspiration, interception and infiltration are relatively unaffected. However, in a high severity area all vegetation is burned, thereby reducing rates of vegetation evapotranspiration and interception to effectively zero, creating hydrophobic ash which impacts rates of infiltration, and alters erosion rates, all of which significantly affect runoff.

Similar to the assessment of peak – peak and both avg – peak RF models and multiple linear regression results varied greatly. The peak – peak RF model explained approximately 50 percent of the total variance while the multilinear regression explained 59 percent. Additionally, the peak – peak metric and area burned at high or moderate severity linear regression produced even greater explanatory power with approximately 75 percent of the total variance explained ($p < 0.01$, Fig. 3-7). This indicates an important relationship between changes in extreme flows and burn severity was underestimated by the RF model.

We speculate that the inconsistency between the two models, RF and linear regression, for the runoff ratio metrics is due to a common problem of RF models. RF models may over-fit the relationship between response and predictor variables. This occurs in cases in which RF tries to correspond too closely to the dataset, therefore it loses the ability to generalize well (Strobl et al., 2009). Results may continue to increase in explanatory power with more observations. Future studies should expand on this research by including more fires to increase model accuracy to test relationships between significant predictor variables.

This study shows that fires significantly impact hydrologic regimes in different ways that a single metric is unable to capture, which may lead to an inaccurate prediction of hydrologic response. Land managers need to be aware of the different ways hydrologic regimes may change based on fire characteristics and the impacts those changes may have on the landscape so that they can apply multiple metrics to more accurately predict hydrologic responses in a specific area. More accurate prediction of hydrologic responses will allow land managers to design and implement more effective restoration measures. To refine change in runoff prediction, more work should be done to further examine the relationships between geologic and fire characteristics and runoff ratios by including additional fire sites that incorporate a wider variety of landscape types.

5. Conclusion

Runoff ratios change after wildfire, and the magnitude and type of change are quantifiable through different methods. Generally, fire, forest, and geologic characteristics influence increases in the magnitude of runoff ratio change at predictable intervals, however using only one metric of analysis may cause miscalculations of landscape response. Understanding how readily available metrics, such as burn severity, porosity, and precipitation, help to develop improved predictive modeling for post-wildfire floods and increase the efficiency of restorative management. More work should be done to better understand the explanatory power of individual variables on a broader area to identify additional influential metrics.

References

Abatzoglou, J.T., Kolden, C.A., 2013. Relationships between climate and macroscale area burned in the western United States. Int. J. Wildl. Fire 22, 1003–1020. https://doi.org/10.1071/WF13019

Benavides-Solorio, J. de D., MacDonald, L.H., 2005. Measurement and prediction of post-fire erosion at the hillslope scale, Colorado Front Range. Int. J. Wildl. Fire 14, 457. https://doi.org/10.1071/wf05042

Benavides-Solorio, J., MacDonald, L.H., 2001. Post-fire runoff and erosion from simulated rainfall on small plots, Colorado Front Range. Hydrol. Process. 15, 2931–2952. https://doi.org/10.1002/hyp.383

Bonfils, C., Santer, B.D., Pierce, D.W., Hidalgo, H.G., Bala, G., Das, T., Barnett, T.P., Cayan, D.R., Doutriaux, C., Wood, A.W., Mirin, A., Nozawa, T., 2008. Detection and attribution of temperature changes in the mountainous Western United States. J. Clim. 21, 6404–6424. https://doi.org/10.1175/2008JCLI2397.1

Breiman, L., 2001. Random forests. Ensemble Mach. Learn. Methods Appl. 45, 5–32. https://doi.org/10.1023/A:1010933404324

Cardenas, M.B., Kanarek, M.R., 2014. Soil moisture variation and dynamics across a wildfire burn boundary in a loblolly pine (Pinus taeda) forest. J. Hydrol. 519, 490–502. https://doi.org/10.1016/j.jhydrol.2014.07.016

Cerrelli, G.A., 2005. FIRE HYDRO, a simplified method for predicting peak discharges to assist in the design of flood protection measures for western wildfires. In: Moglen, Glenn E., eds., in: 2005 Watershed Management Conference-Managing Watersheds for Human and Natural Impacts: Engineering, Ecological, and Economic Challenges. pp. 935–941.

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Kyle, T., Gibson, J., Lawler, J.J., Beard, H., Hess, T., 2007. Random Forests for Classification in Ecology Published by : Ecological Society of America. Ecology 88, 2783–2792.

DeBano, L.F., 1981. Water repellent soils: a state-of-the-art. Gen. Tech. Rep. PSW-GTR-46 1–21.

Dunkerley, D., 2012. Effects of rainfall intensity fluctuations on infiltration and runoff: Rainfall simulation on dryland soils, Fowlers Gap, Australia. Hydrol. Process. 26, 2211–2224. https://doi.org/10.1002/hyp.8317

Foufoula-Georgiou, E., Belmont, P., Wilcock, P.R., Gran, K.B., Finlay, J.C., Kumar, P., Czuba, J.A., Schwenk, J., Takbiri, Z., 2016. Comment on "Climate and agricultural land use change impacts on streamflow in the upper midwestern United States" by Satish C. Gupta et al. Water Resour. Res. 52, 7523–7528. https://doi.org/10.1002/2015WR017200.A

Hawkins, R.H., Greenberg, R.J., 1990. WILDCAT4 Flow Model. [This edition further enhances Moore's version]. Sch. Renew. Nat. Resour. Univ. Arizona, Tucson, AZ.

Hidalgo, H.G., Das, T., Dettinger, M.D., Cayan, D.R., Pierce, D.W., Barnett, T.P., Bala, G., Mirin, A., Wood, A.W., Bonfils, C., Santer, B.D., Nozawa, T., 2009. Detection and attribution of streamflow timing changes to climate change in the Western United States. J. Clim. 22, 3838–3855. https://doi.org/10.1175/2009JCLI2470.1

Higgins, B., Jarnecke, J., 2007. Salt Creek BAER-2007 Burned Area Emergency Response.

Horton, R.E., 1945. Erosional development of streams and their drainage basins, hydrophysical approaches to quantitative morphology. Geol. Soc. Am. Bull. 56, 275–370.

Huffman, E.L., MacDonald, L.H., Stednick, J.D., 2001. Strength and persistence of fire-induced soil hydrophobicity under ponderosa and lodgepole pine, Colorado Front Range. Hydrol. Process. 15, 2877–2892. https://doi.org/10.1002/hyp.379

Knighton, D., 1998. Fluvial Forms & Processes, Fourth. ed. Routledge, New York.

Kolden, C.A., Lutz, J.A., Key, C.H., Kane, J.T., van Wagtendonk, J.W., 2012. Mapped versus actual burned area within wildfire perimeters: Characterizing the unburned. For. Ecol. Manage. 286, 38–47. https://doi.org/10.1016/j.foreco.2012.08.020

Kolden, C.A., Smith, A.M.S., Abatzoglou, J.T., 2015. Limitations and utilisation of Monitoring Trends in Burn Severity products for assessing wildfire severity in the USA. Int. J. Wildl. Fire 24, 1023–1028. https://doi.org/10.1071/WF15082

Kuyumjian, G., n.d. Greg's Curve Number thoughts.

Li, F., Lawrence, D.M., 2017. Role of fire in the global land water budget during the twentieth century due to changing ecosystems. J. Clim. 30, 1893–1908. https://doi.org/10.1175/JCLI-D-16-0460.1

Link, T.E., Unsworth, M., Marks, D., 2004. The dynamics of rainfall interception by a seasonal temperate rainforest. Agric. For. Meteorol. 124, 171–191. https://doi.org/10.1016/j.agrformet.2004.01.010

Livingston, Russell, K., Earles, T.A., Wright, K.R., 2005. Los Alamos post-fire watershed recovery: a curve-number-based evaluation.In: Moglen, Glenn E., eds., in: 2005 Watershed Management Conference-Managing Watersheds for Human and Natural Impacts: Engineering, Ecological, and Economic Challenges. Williamsburg, VA. Alexandria, VA, pp. 471–481.

Mallik, A.A.U., Gimingham, C.H., Rahman, A.A., 2016. Ecological Effects of Heather Burning : I . Water Infiltration , Moisture Retention and Porosity of Surface Soil Published by : British Ecological Society Stable URL : http://www.jstor.org/stable/2259530 Accessed : 01-03-2016 05 : 15 UTC Your use of the J 72, 767–776.

Malmon, D. V., Reneau, S.L., Katzman, D., Lavine, A., Lyman, J., 2007. Suspended sediment transport in an ephemeral stream following wildfire. J. Geophys. Res. Earth Surf. 112, 1–16. https://doi.org/10.1029/2005JF000459

Moody, J.A., Martin, D.A., 2001. Initial hydrologic and geomorphic response following a wildfire in the Colorado front range. Earth Surf. Process. Landforms 26, 1049–1070. https://doi.org/10.1002/esp.253

Moody, J.A., Shakesby, R.A., Robichaud, P.R., Cannon, S.H., Martin, D.A., 2013. Current research issues related to post-wildfire runoff and erosion processes. Earth-Science Rev. 122, 10–37. https://doi.org/10.1016/j.earscirev.2013.03.004

Oki, T., 2006. Global Hydrological Cycles and World Water. Science (80-.). 1068–1073.

Olson, J.R., Hawkins, C.P., 2012. Predicting natural base-flow stream water chemistry in the western United States. Water Resour. Res. 48, 1–19. https://doi.org/10.1029/2011WR011088

Phillips, R.W., Spence, C., Pomeroy, J.W., 2011. Connectivity and runoff dynamics in heterogeneous basins. Hydrol. Process. 25, 3061–3075. https://doi.org/10.1002/hyp.8123

Pypker, T.G., Bond, B.J., Link, T.E., Marks, D., Unsworth, M.H., 2005. The importance of canopy structure in controlling the interception loss of rainfall: Examples from a young and an old-growth Douglas-fir forest. Agric. For. Meteorol. 130, 113–129. https://doi.org/10.1016/j.agrformet.2005.03.003

Renard, K.G., Foster, G.R., Weesies, G.A., Mccool, D.K., Yoder, D.C., 2000. <CAT10827029PDF.pdf>.

Reneau, S.L., Katzman, D., Kuyumjian, G.A., Lavine, A., Malmon, D. V., 2007.

Sediment delivery after a wildfire. Geology 35, 151–154. https://doi.org/10.1130/G23288A.1

Robichaud, P.R., Brown, R.E., 1999. No Title, in: What Happened after the Smokecleared: Onsite Erosion Rates after a Wildfire in Eastern Oregon. in:Olsen, D.S., Potyondy, J.P. (Eds.), Proceedings Wildland Hydrol-Ogy Conference, June 1999, Bozeman, Mt Hernon, Virginia.American Water Resource Association. pp. 419–426.

Schlosser, C.A., Strzepek, K., Gao, X., Fant, C., Blanc, É., Paltsev, S., Jacoby, H., Reilly, J., Gueneau, A., 2014. The future of global water stress: An integrated assessment. Earth’s Futur. 2, 341–361. https://doi.org/10.1002/2014ef000238

Schoennagel, T., Veblen T. T., Romme W. H., 2004. The Interaction of Fire, Fuels, and Climate across Rocky Mountain Forests. Bioscience 54, 661. https://doi.org/10.1641/0006-3568(2004)054[0661:TIOFFA]2.0.CO;2

Schottler, S.P., Ulrich, J., Belmont, P., Moore, R., Lauer, J.W., Engstrom, D.R., Almendinger, J.E., 2014. Twentieth century agricultural drainage creates more erosive rivers. Hydrol. Process. 28, 1951–1961. https://doi.org/10.1002/hyp.9738

Springer, E.P., Hawkins, R.H., 2005. Curve Number and Peakflow Responses Following the Cerro Grande Fire on a Small Watershed 836, 1–12. https://doi.org/10.1061/40763(178)40

Stoof, C.R., Wesseling, J.G., Ritsema, C.J., 2010. Effects of fire and ash on soil water retention. Geoderma 159, 276–285. https://doi.org/10.1016/j.geoderma.2010.08.002

Story, M., 2003. Stormflow methods.

Strobl, C., Malley, J., Tutz, G., 2009. An Introduction to Recursive Partitioning: Rationale, Application, and Characteristics of Classification and Regression Trees, Bagging, and Random Forests. Psychol. Methods 14, 323–348. https://doi.org/10.1037/a0016973

Stuart, B., 2000. Maudlow Fire, Burned Area Emergency Rehabilitation (BAER) plan.

Stuebe, M., Johnson, D.M., 1990. Runoff volume estimation using GIS techniques. Water Resour. Bull. 26, 611–620.

Tedela, N.H., McCutcheon, S.C., M.ASCE, P.E., Rasmussen, T.C., Hawkins, R.H., F.ASCE, P.E., Swank, W.T., Campbell, J.L., Adams, M.B., Jackson, C.R., Tollner, E.W., P.E., 2011. Pressure Flushing of Cohesive Sediment in Large Dam Reservoirs. J. Hydrol. Eng. 17, 1188–1198. https://doi.org/10.1061/(ASCE)HE

USDA Forest Service - RMRS - Moscow Forestry, 2013. Burned Area Emergency

Response Tools [WWW Document]. URL https://forest.moscowfsl.wsu.edu/BAERTOOLS/ROADTRT/Peakflow/CN/supplement.html#Cerrelli2005 (accessed 7.3.19).

Vörösmarty, C.J., Green, P., Salisbury, J., Lammers, R.B., 2000. Global Water Resources : Vulnerability from Climate Change and Population Growth Contemporary Population Relative to Demand per Discharge. Science (80-.). 289, 284–288. https://doi.org/10.1126/science.289.5477.284

Vörösmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S.E., Sullivan, C.A., Liermann, C.R., Davies, P.M., 2010. Global threats to human water security and river biodiversity. Nature 467, 555–561. https://doi.org/10.1038/nature09440

Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase Western U.S. forest wildfire activity. Science (80-.). 313, 940–943. https://doi.org/10.1126/science.1128834

White, D., 1988. Grid-based application of runoff curve numbers. J. Water Resour. Plan. Manag. 114, 601–612.

Wine, M.L., Makhnin, O., Cadol, D., 2018. Nonlinear Long-Term Large Watershed Hydrologic Response to Wildfire and Climatic Dynamics Locally Increases Water Yields. Earth’s Futur. 6, 997–1006. https://doi.org/10.1029/2018EF000930

Woods, S.W., Balfour, V.N., 2008. The effect of ash on runoff and erosion after a severe forest wildfire, Montana, USA. Int. J. Wildl. Fire 17, 535–548. https://doi.org/10.1071/WF07040

CHAPTER 4

AN INITIAL ANALYSIS OF WILDFIRE INPACTS ON RIVERBED GRAIN SIZE IN RELATION TO SALMONID HABITAT

Abstract

Wildfires change hydrology, hillslope erosion, and stream channel sediment transport, which significantly impact salmonid habitat at various life stages, including females' ability to dig redds, successful incubation, and alevin emergence. We use riverbed grain size as a proxy for change in habitat quality in order to assess wildfire impacts at these various life stages. We focus on two fires, Dollar Ridge, UT (2018), and Trail Mountain, UT (2018). We visit established sites post-fire, but prior to any significant rainfall event, and post-fire, post-precipitation. We take aerial photographs and conduct pebble counts following the CHaMP protocol. A Chi-squared test determines changes in riverbed grain size between each site pre- and post-precipitation. We define and quantify changes in five habitat quality metrics: 1) change in proportion of movable grain sizes using 10% guideline for both Brown and Cutthroat Trout, 2) change in movable grain sizes using Functional Mobility power equation, 3) change in grain size less than two mm, 4) change in grain size less than 11 mm, and 5) change in grain size between 11mm and largest movable grain. We run Random Forest models on each metric to identify important environmental variables affecting that metric. Results indicate sites at both fires changed most significantly in grain size proportion in areas that were steep, burned, or directly downstream of a burned area, and received precipitation. The five metrics reveal inconsistencies when measuring similar habitat metrics; metrics 1 and 2 do not provide consistent results even though they are both measuring the proportion of

movable grain size. Additionally, the quality of change is different at each site for the various metrics, showing that no one metric can capture a complete analysis of change in habitat. Metric 5, which considers the requirements of all three life stages, indicates that most areas decrease, or do not change, in habitat quality. Random Forest did not generate a significant model or produce high explanatory variables. As fires increase, more salmonid habitat will be affected and at risk for habitat degradation. More analysis of how riverbed grain size changes after a fire is needed to allow managers to design and enact effective mitigation and restoration practices.

1. Introduction

Climate change threatens salmonid populations across the western United States as the wildfire season lengthens and the frequency, and area continue to increase (Prudencio et al., 2018; Shepard et al., 2005; Wenger et al., 2011; Westerling et al., 2006; Williams et al., 2009). Wildfires substantially increase delivery of water and sediment supply to rivers, thereby changing the flows, sediment transport and grain size distribution on the river bed. Changes in grain size distribution are particularly problematic as it affects salmonids at multiple life stages including: redd construction, embryo incubation, and alevin emergence (Benda et al., 2003; Kondolf, 2000). Conservation efforts across the western US aim to maintain native salmonid populations, but these efforts are unlikely to offset disturbances caused by climate change. Therefore, large declines in native salmonid populations are imminent (Wenger et al., 2011; Williams et al., 2009). In order to curtail impending declines in salmonid populations and provide guidance for effective restoration and mitigation practices, there is a pressing need to understand how wildfires change the riverbed grain size, and how those changes affect the quality of salmonid habitat.

Post-wildfire changes in stream hydrology, hillslope erosion, and stream channel sediment transport have negative direct impacts on fish populations, often causing local extirpation (Brown et al., 2001; Gresswell, 1999; Propst and Stefferud, 1997; Roghair et al., 2002). Wildfires kill vegetation and create hydrophobic ash, both of which lead to significant increases in the proportion of rainfall that becomes runoff (i.e., the rainfall-runoff ratio) as well as increases in overland flow, which causes surface erosion by process of sheetwash and gullying (Larsen et al., 2009; Wagenbrenner and Robichaud, 2014; Woods and Balfour, 2008). Catastrophic erosion events, such as debris flows or hyperconcentrated flows, are likely to occur in severely burned areas (Cannon, 2001; Staley et al., 2017). These changes in sediment and flow regimes impact the quality of fish habitat for many kilometers downstream. Large pulses of sediment contributed to the channel following a wildfire are often severely detrimental to fish habitat in the short term. However, longer term effects of post-wildfire erosion on fish habitat may be positive or negative (Sedell et al., 2015). For example, large amounts of fine sediment (e.g., sand) may degrade habitat by reducing topographic and hydraulic complexity, covering up spawning gravels and filling pores. However, mass sediment transport can also restore habitat conditions for systems that have insufficient sediment supply. The input of large grains and boulders into the channel create pockets consisting of larger framework grains and slower moving water, thus increasing refugia for spawning, rearing and feeding (Copp, 1989; Everest and Meehan, 1981; Reeves et al., 1995).

To link the impact of forest fires to habitat functionality, it is important to understand how the structure of the river bed will change when forest fires disturb the sediment and flow regimes. River bed substrate is characterized by framework and matrix grains. Framework grains are larger particles that create voids within the substrate, and matrix grains are finer-sized particles that fill in the voids of the framework. The threshold size between matrix sediment and framework grains is a function of pore size in the framework (Kondolf, 2000). Characteristics of the bed surface and subsurface are important indicators of habitat quality because different phases of the salmonid life cycle depend on different attributes of the bed structure; such as the size of framework grains, the proportion of matrix present, and the pore space.

Different grain sizes affect salmonids at various life stages. Spawning females must be able to move grains and create a redd for depositing eggs (Fig. 4-1). Thus, a large

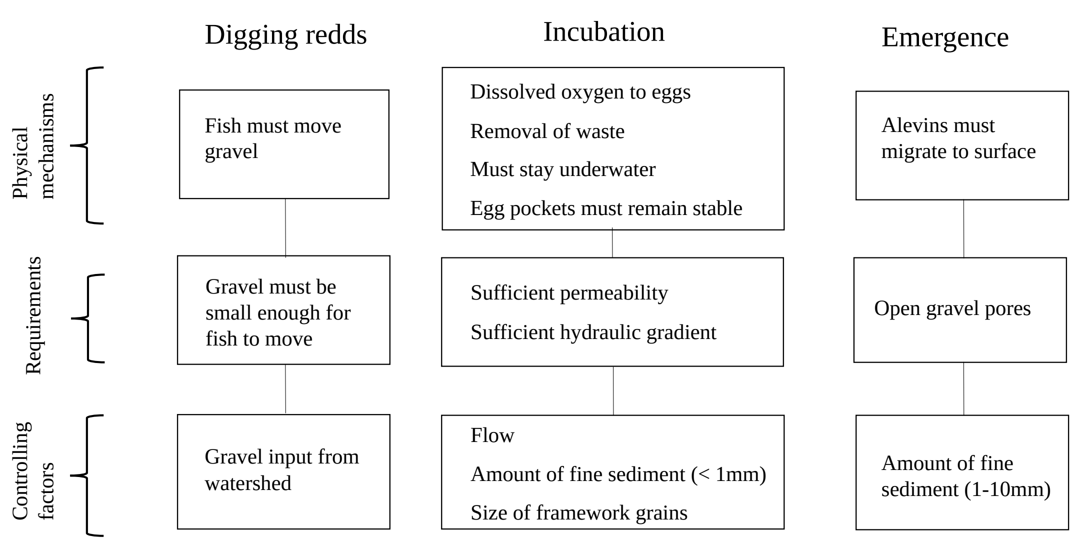

Fig. 4-1. Conceptual diagram of how physical mechanisms, requirements and controlling factors affect ability to dig redds, incubation, and emergence (modified from Kondolf, 2000).

proportion of the framework grains should be movable, and this creates an upper limit on the grain size of framework particles in optimal spawning habitat (Kondolf, 2000).

Successful embryo incubation depends on sufficient pore space in the matrix so that water can flow freely though the gravel to bring dissolved oxygen to the eggs and carry away metabolic waste (Fig. 4-1) (Greig et al., 2007). Decreased permeability leads to less intergravel flow and a decreased delivery of dissolved oxygen, sometimes leading to embryo suffocation. Therefore, the amount of interstitial matrix present and the effect it has on permeability defines the lower limit of spawning gravel size (Kondolf, 2000). Grain sizes less than one mm are known to reduce permeability (Cederholm and Salo, 1979; Tagart, 1984), and field observations indicate that less than 12-14 % of grains should be less than approximately one mm for successful incubation (Cederholm and Salo, 1979; Kondolf, 2000; McNeil and Ahnell, 1964). However, the proportion of fine sediment present that negatively impacts incubation varies between studies and one mm is not a rigid constraint (Kondolf, 2000).

Once embryos hatch, alevins within the matrix migrate to the surface of the riverbed, thus adequate pore space must be present for alevins to emerge successfully (Figure 1). When fine sediment blocks pore space, alevins cannot migrate upward, and therefore die (Franssen et al., 2014; Hawke, 1978; Phillips et al., 1975). Sediment size that reduces successful emergence is between 1 and 10 mm; however, this is not a physically rigid constraint, and a threshold for the optimal proportion of grain sizes in this range has not been established in the literature (Bjornn, 1969; Harshbarger and Porter, 1982; Kondolf, 2000; Phillips et al., 1975).

The goal of this study is to determine which environmental characteristics impact salmonid habitat after a wildfire in mid-high elevation forested areas within the western US. To achieve this goal, we address the following research questions:

1) Are there 'hotspots' of change within the stream networks where post-wildfire sediments are especially beneficial or detrimental to salmonid habitat?
2) How does overall grain size distribution change within the stream network post-wildfire?
3) How does the ability of spawning female salmonids to dig redds change within stream networks following a wildfire?
4) How is embryo incubation affected within river networks after wildfire?
5) How does potential for alevin emergence change within river networks after wildfire?

To address these questions, our study focuses on two fires in Utah, Dollar Ridge (2018) and Trail Mountain (2018), to assess post-wildfire mechanisms affecting salmonid habitat. These two fires are of interest because both cover large areas that encompass river networks with thriving, well-monitored fish populations, including salmonid species Cutthroat and Brown Trout populations. We collected grain size and habitat data immediately following the wildfire but before any significant rainfall events, as well as data following significant precipitation events. Specifically, we conducted pebble counts and measured other river bed characteristics to assess changes in grain size distribution. We used Random Forest (RF) statistical models to analyze how fire and watershed characteristics may alter salmonid habitat post-wildfire, taking advantage of RF models' ability to handle complex, nonlinear relationships (Cutler et al., 2007; Olson and

Hawkins, 2012). We used variable importance and partial dependence plots to determine which environmental variables provided the greatest explanatory power for the observed changes in habitat and evaluated form and strength of the relationships between environmental predictors and habitat changes.

2. Study area

The study examined two fires: Dollar Ridge (DR), UT (2018) and Trail Mountain (TM), UT (2018), to assess how fire affects grain size distribution and related characteristics of salmonid habitat. The Dollar Ridge fire was first reported July 1, 2018, and burned 234 km^2 over approximately two months, making it the fourth largest wildfire in Utah state history; however, most of the fire burned at low severity (3% high severity, 28% moderate severity, 47% low severity, and 22% very low/unburned; Fig. 4-2). The burned area included the Strawberry River between Strawberry Reservoir and Starvation Reservoir. We focus our analysis on the impact to salmonid habitat along, and downstream from, the burned section of the Strawberry River.

The Strawberry Pinnacles is a geologic formation located approximately half way between the two reservoirs and acts as a geographic and biotic divide along the Strawberry River. Above the Strawberry Pinnacles, the valley is a semi-irregular shape with shallow soils and exposed bedrock (www.nrcs.usda.gov). The channel is in contact with confining margins. The valley upstream from Strawberry Pinnacles is semi-confined, meaning the channel can meander, but portions of the channel margin are constricted by steep valley walls and bedrock (Brieley and Fryirs, 2005; Fryirs et al., 2016). Human development is limited along the upper reach with the exception of a mostly gravel road that runs along the entire valley corridor and a few privately-owned cabins occupied during summer months. On north facing slopes, pre-fire vegetation consisted primarily of spruce-fir forests (Birchell et al., 2014). Upland vegetation consisted of sagebrush, mountain mahogany, pinyon and juniper. The riparian corridor consisted of willow, narrowleaf cottonwood, western red birch, red twig dogwood, skunk bush and box elder maple. The riparian zone is well-developed, providing undercut banks, overhanging vegetation, and woody debris, providing optimal trout habitat (Birchell et al., 2014). Prior to the fire, this portion of the river had a well-defined pool and riffle habitat with sparse deep runs (Team, 1998). Upper Strawberry River primarily provides habitat to Brown and Cutthroat Trout.

Below the Strawberry Pinnacles, the valley is semi-confined, but the confining margins are wider than upstream, allowing the river more room to meander. Consistent with soils above the Pinnacles, the watershed draining to this downstream reach is also characterized by shallow soils and exposed bedrock (www.nrcs.usda.gov). This portion of the river flows through private property used for cultivated fields of alfalfa hay and pastures. (Birchell et al., 2014; Team, 1998). Riparian vegetation in the downstream reach is the same as the upstream reach (willow, narrowleaf cottonwood, western red birch, red twig dogwood, skunk bush and box elder maple) with the addition of invasive tamarisk, which grows along the banks (Birchell et al., 2014). Upland vegetation is comprised of drier desert species such as pinyon, juniper, sagebrush, greasewood, mormon tea and rabbit brush (Birchell et al., 2014) The lower Strawberry River provides habitat for Brown Trout, Cutthroat Trout, Rainbow Trout, Bluehead Sucker, Mountain Sucker, and Mountain Whitefish.

The Trail Mountain Fire started June 6, 2018, and burned approximately 72 km^2 over two months. Compared to the Dollar Ridge fire, a larger proportion of this fire burned at high to moderate burn severity, with 38% high severity, 40% moderate, 14% low and 8% very low or unburned (Fig. 4-2). This study focuses on Crandall Canyon Creek located in Crandall Canyon. Also located in this study area is Crandall Canyon Mine, which has been abandoned for 12 years. Upstream of the mine there has been no anthropogenic influence, and there are no roads leading up the canyon. Crandall Canyon is characterized as a confined valley because the channel has very limited capacity to adjust or meander (Fryirs et al., 2016). Soils depth ranges from moderate to very deep, and primarily consists of loamy soil mixed with larger particles, such as rock fragments, cobbles and gravel (UF Forest Service, 2018). Canyons are steep and densely vegetated by deciduous forests (US Forest Service, 2019). Near the mouth of the canyon, near the mine, there are patches of conifer forest, comprised of spruce/fir mixed forest and woodlands, dominated by pinyon-juniper. Vegetation becomes sparser downstream and is dominated by herbland, moist to dry meadows. Habitat in Crandall Creek is predominately step-pool morphology and the dominant populations are brown and cutthroat trout.

3. Methods

We focused on five site locations within each fire study area (Fig. 4-2). Sites were selected based on several factors, including: burn severity, susceptibility to debris flows, (determined using the BEAR assessment report), and accessibility. We visited each site twice: once prior to the first precipitation event following the fire, and again after the first significant precipitation event occurred. We used photos and grain size distribution data

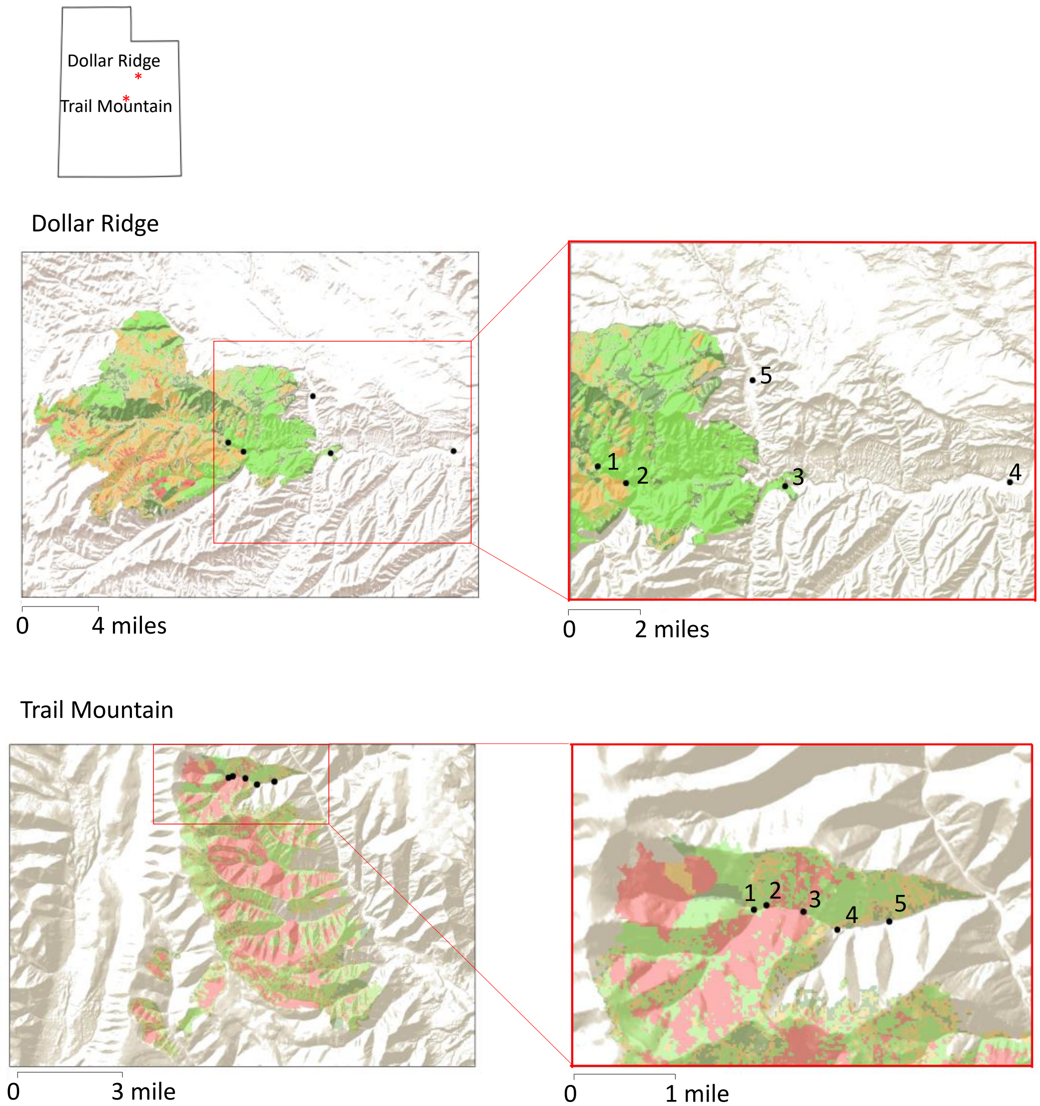

Fig. 4-2. Burn severity maps and site locations for each fire. Burn severity classifications include high (red), moderate (orange), low (light green) and very low/unburned (dark green).

to assess landscape change, various metrics of fish habitat, movability of grains by spawning fish, excessive fines inhibiting incubation, excessive sedimentation inhibiting emergence, and overall grain size distribution changes. We obtained average fish length information from the Utah Division of Wildlife Resources reports to generate assessment of habitat needed for local fish populations (1989, 1998, 2014, 2017, 2019). We used numerous metrics of salmonid habitat because, while each of these methods are widely accepted and used, no single method is capable of representing how each life stage is impacted by sediment size distribution changes. Therefore, even though some metric measurements overlap, it is necessary to use an array of habitat quality metrics to accurately quantify the impact of changes in bed grain size at all life stages.

3.1 Qualitative landscape change

Qualitative observations allowed us to determine what mechanism of sediment transport delivered sediment into the system as well as the location and frequency of sediment inputs. We conducted unmanned aerial vehicle (UAV) surveys using a DJI Phantom 4 during each site visit to qualitatively assess changes in channel morphology, such as changes in bars or islands, channel migration, differences in vegetation and woody debris, and differences in the presence of large grains or boulders, along the Strawberry River and Crandall Canyon Creek. UAV photos were stitched together using Photoshop software. Vegetation restricts photo quality at some Trail Mountain sites.

3.2 Sample and assessment of gravel size distributions

We conducted pebble counts at each site using a standard gravelometer, recording grain size, percent embeddedness of each selected grain, and percent area of each selected grain surrounded by fines for 110 grains (CHaMP, 2016). All three metrics are commonly used, but there are important limitations (CHaMP, 2016). Traditional pebble counts indicate the distribution of framework grains, and thus the availability of spawning gravels, however they do not capture interstitial spaces. Percent fines provides insight into spawning habitat for successful incubation and emergence, however, this method may still underestimate the percent fines present. To help mitigate underestimation and cross-validate changes within the matrix, we also measured percent embeddedness. Percent embeddedness also captures pore spaces within the matrix affecting incubation and emergence (CHaMP, 2016). Thus, we used all three metrics to accurately capture relevant distributional changes in both framework and matrix grains. Pebble counts were located in riffles along 11 transects with ten counts in each transect (CHaMP, 2016). To determine if the grain size had changed at each site between visit one and visit two, we used a two-sided, two-sample Kolmogorov-Smirnov (K-S) test, a built-in function in R (https://www.rdocumentation.org/packages/dgof/versions/1.2/topics/ks.test). The K-S test is a nonparametric, probability distribution test; it does not assume any underlying distribution of the data. Assumptions of the K-S test are: 1) samples are drawn randomly from the same set of values and are mutually independent, and 2) the data is measured by ordinal or continuous scales. One benefit of using a K-S test is that it is sensitive to differences in distributional characteristics, such as location, dispersion and shape of the distribution, meaning that it can detect differences in any and/or all characteristics. However, the K-S test does not indicate which characteristic has changed.

3.3 Determine if spawning females can move gravel

We calculated moveable grain sizes for both Cutthroat and Brown Trout surrounding Dollar Ridge and Trail Mountain areas using multiple techniques. We used the average fish length of the entire sampled population to generalize body length of spawning females because fish length according to specific age and gender is not available.

There are several commonly used methods to determine the optimal grain size for spawning, given the fish body size. The ‘10% guideline method’ characterizes the grain size of mobility as approximately 10% of fish’s body length (Kondolf, 2000). Thus, the upper size limit of movable grains scales with fish size. The 10% guideline uses the D_{50}, the median diameter grain size, of bed material to determine if spawning females can successfully build redds in a reach of the river. We classified whether the reach is movable or immovable for each site visit to assess changes in the classification and habitat quality. If the D_{50} of bed material was greater than 10% of the average length for each species, we classified the river reach as immovable, if it was less than 10%, we classified it as movable. If the site was movable in the first visit and immovable in the second visit, there was a decrease in habitat quality and the proportion of movable grains. Conversely, if the site was immovable in the first visit and moveable in the second visit, there was an increase in habitat quality and movable grains. If the classification of each visit was consistent between visits, or the proportion of movable grains was within five percent during each visit, we characterized the site as not having changed.

A second way to determine what grain size a spawning fish can move is the functional area (F_m). This method has been recently established through extensive field experiments with various salmonid species (Overstreet et al., 2016; Riebe et al., 2014). F_m is defined as the percentile of the of the largest movable grain size from the cumulative grain size distribution. The largest moveable grain size, D_T, is defined using $115(L/600)^{0.62}$, where L is the body length of the fish (Riebe et al., 2014; Overstreet et al., 2016). We used relative changes in F_m to assess habitat changes at each site and assumed that there is no threshold for proportion of gravel that needs to be movable for optimal habitat. If F_m

increased between visit 1 and visit 2, we characterized the site as having increased in proportion of movable grains, interpreted as an increase in quality. If F_m decreased, the site decreased in proportion of movable grains, interpreted as a decrease in quality. If F_m is within five percent between visit 1 and visit 2, we characterized the site as not having changed.

3.4 Determine spatial availability to build redds

In addition to being able to move the present grains, spawning females need space to dig their redds. To determine if spatial availability changed between site visits one and two, we assessed spawning capacity (N_{redds}), defined as the number of redds that a salmonid can build per unit area. Spawning capacity is calculated as F_m/A_{redds} X 100 where $A_{redds} = 3.3[L/600]^{2.3}$ and L is the length of the fish (Riebe et al., 2014; Overstreet et al., 2016). We calculated N_{redds} for both Cutthroat and Brown Trout and compared N_{redds} between visit 1 and visit 2 at each site. If N_{redds} increased, we characterized the site as having increased in spawning capacity. If N_{redds} decreased, the site decreased in spawning capacity. If N_{redds} of visit 1 was within five percent of visit 2, we characterized the site as not having changed.

3.5 Determine if incubation is affected

Standard methods of assessing successful egg incubation habitat indicate that approximately 12-14 % of the grain size distribution should not be finer than 1mm (McNeil and Ahnell, 1964; Tappel and Bjornn, 2004). However, this is an arbitrary cutoff and is not a physically significant threshold (Kondolf, 2000). For field measurements we used a standard gravelometer, which only measures grains down to 2 mm. Thus, the change in the proportion of < 2 mm grains represents our measure of the proportion of fines that may impact incubation. To analyze if incubation is affected by the input of sediment following forest fires, we compared the proportion of fines present during both site visits. Working under the assumption that > 14% fines is detrimental to fish habitat, we classified the proportion of changes in fines into five categories: (1) no cross of 14 % threshold between visits, interpreted as no habitat change (2) cross of 14 % threshold: increase of fines between visits, interpreted as habitat degradation (3) cross of 14 % threshold: increase in fines but proportions between visits were within five percent of each other, interpreted as slightly decreased habitat quality (4) cross of threshold: decrease of fines between visits, interpreted as increased habitat quality (5) cross of 14 % threshold: decrease in fines but proportions between visits are within five percent of each other, interpreted as slightly increased in habitat quality. Categories 3 and 5 were added in case the difference in proportion between visit 1 and visit 2 is not significant; however, the threshold change should still be noted.

3.6 Determine if emergence is affected

The proportion of larger grains affecting the success of emergence varies considerably between studies and is difficult to define (Kondolf, 2000). There is no established threshold for river bed grain sizes ranging from 1-10 mm that negatively affect habitat quality. Additionally, there is no physical or ecological basis to suggest that 10 mm is a rigid threshold. Thus, as suggested by Kondolf (2000), we assessed if optimal habitat for emergence success changed by comparing the proportion of the bed occupied by 2-11 mm between visit 1 and visit 2. We used 11 mm instead of 10 mm to coincide with the available data, which was collected using a standard gravelometer. If the proportion of grain sizes between 2 to 11mm increased, we determined that the site became less suitable for successful emergence. If the proportion of grains sizes between 2 to11 mm decreased, habitat became more suitable for successful emergence. If the proportions stayed within five percent of the first measurement, there was no significant change.

3.7 Changes in optimal grain size proportion

Standard methods for assessing the quality of spawning gravel do not account for specific changes in fines, which could lead to inaccurate results in habitat assessment, especially in areas prone to fining, such as after wildfires. To incorporate the effects of fines in our habitat quality metrics, we calculated the proportion of functional grain sizes for suitable fish habitat. We defined the proportion of functional grain sizes as the fraction of the grain size distribution that is beneficial for spawning habitat, and a change in proportion of functional grain size indicates a change in habitat quality. Because it is well established in the literature that grain size < 1 mm inhibit incubation and < 10 mm can hinder emergence, we considered the proportional change in grains that are large enough not to hinder incubation or emergence success, but small enough for spawning females to move. As in the emergence analysis, we used 11 mm as that is the closest size class on a standard gravelometer. We used D_T, calculated above, to determine the largest moveable grain size (Riebe et al., 2014; Overstreet et al., 2016). We classified the site as increased quality if the proportion increased, decreased quality if the proportion decreased, and no change if the proportion between visits were within five percent of one another.

3.8 Random Forest analysis

We used Random Forest (RF) models to identify important predictor variables, such as fire, channel or watershed characteristics, that control changes in different metrics of habitat quality. RF models partition data to choose predictor variables that best explain the variance observed in the response variables (for a full description of RF models, see Chapter 2- Methods). Chapter 2 utilized RF in regression mode, whereas this chapter utilizes RF in classification mode. Classification RF models differ from regression RF models in that classification models use a response group based on class membership while regression RF models use a numerical value. Additionally, classification models use the "Gini" index to measure homogeneity within each node. The Gini index measures the frequency of each class within each node until homogeneity within each daughter node is achieved (Strobl et al., 2009).

We constructed seven separate RF models for the following response variables: 1) 10% guideline- Brown Trout; 2) 10% guideline- Cutthroat Trout; 3) F_m; 4) spawning capacity; 5) incubation; 6) emergence; and 7) optimal grain size proportion. We used 500 trees to construct each model as increasing or decreasing the number of trees did not influence our results. Additionally, we used $p^{0.5}$, where p is the total number of predictor variables in the model, to determine the number of predictor variables available at each node split. We used the randomForest package in R statistical computing software to complete these analyses (https://cran.r-project.org/web/packages/randomForest/randomForest.pdf). To determine important predictor variables, we generated variable importance plots for each RF model, and used an iterative modeling approach (Olson and Hawkins, 2012) to eliminate unimportant variables, leaving only the most important variables in our model. To measure model performance, we generated a kappa statistic for each model to determine randomness. Kappa is a correlation coefficient, defined as the amount of variation in the dependent variable (habitat quality change) explained by the independent variable (important predictor variables determined by the RF model) and can range from -1 to 1 (Cohen, 1960; McHugh, 2012). If the kappa statistic is less than $K < 0.59$, we determined that the RF model performance was weak (McHugh, 2012), and that the RF model classified predictions onto the out-of-bag samples correctly due to random chance. If $K > 0.60$ we determined that the RF model is reliable. Partial dependence plots for each important predictor variable allowed us to assess the relationship between the response and important predictor variables.

The input (predictor) variables of our RF models are environmental variables extracted from StreamCat (https://www.epa.gov/national-aquatic-resource-surveys/streamcat), which includes watershed, vegetation, and geologic characteristics. We also used fire perimeter and burn severity data sourced from USDA Forest Service Burn Area Emergency Response team (BAER; https://fsapps.nwcg.gov/afm/baer/download.php). We used BAER data to calculate fire characteristics, such as percent of upstream basin burned at high and moderate severity, burn severity at the sample site location, and total upstream area burned (Table 4-1).

4. Results

Significant geomorphic changes occurred at both Dollar Ridge and Trail Mountain sites. Heavy rainfall and subsequent debris flows in the Dollar Ridge study area delivered large amounts of sediment into the Strawberry River. Debris flows occurred at

Table 4-1
List of sites and selected associated data.

Site	Upstream area burned at high severity (%)	Upstream area burned at moderate severity (%)	Total upstream area burned (%)	Severity of burn at site location	D_{50} visit 1	D_{50} visit 2
DR1	3	35	33	Moderate	64	11
DR2	3	36	35	Moderate	32	1
DR3	3	28	25	Moderate	45	32
DR4	3	28	24	Unburned	64	45
DR5	0	23	14	Unburned	45	45
TM1	7	52	68	Moderate	16	8
TM2	3	50	83	High	11	8
TM3	3	50	85	High	39	8
TM4	2	49	85	Moderate	39	32
TM5	2	44	72	Unburned	45	32

and between sites DR1 and DR2. Unburned downstream sites on the Strawberry River changed less dramatically in grain size distributions and river morphology compared to sites that were closer to, or within, the burned area. Rainfall was sparse in the Trail Mountain study area resulting in less substantial landscape changes, but sheetwash, rilling and gullying still occurred, delivering fine sediment into the system. Similar to Dollar Ridge sites, downstream unburned areas did not qualitatively change in grain size distribution or river morphology.

The various metrics contradict one another in regard to changes in habitat quality, even when similar habitat characteristics are being described. General trends indicate that habitat is likely to remain unchanged or decrease in quality (Table 4-2). However, depending on the metric used to assess habitat quality, there are some locations where we observe increases in habitat quality. RF models only explain an acceptable amount of the

Table 4-2
Results table of analyzed metrics of fish habitat quality. “D” indicates decreases in habitat, quality, “I” indicates increases in habitat quality, and “NC” indicates no change in habitat quality.

Site	10% Guideline-Brown Trout	10% Guideline-Cutthroat Trout	F_m	N_{redds}	Incubation	Emergence	Functional grain size proportion
DR1	I	NC	I	I	D	D	D
DR2	I	NC	I	I	NC	D	D
DR3	NC	NC	I	I	NC	D	NC
DR4	NC	NC	I	I	NC	D	NC
DR5	NC	NC	D	D	NC	D	D
TM1	NC	NC	D	D	NC	D	D
TM2	NC	NC	D	D	NC	I	NC
TM3	NC	I	I	I	NC	D	NC
TM4	NC	NC	D	D	NC	D	D
TM5	NC	NC	D	D	I	D	D

variance in habitat changes using environmental predictor variables for the ‘10% guideline’ for Brown Trout.

4.1 Qualitative landscape change

Using qualitative assessment, we identified geomorphic changes and sediment transport mechanisms along both Strawberry River and Crandall Canyon Creek which significantly altered the landscapes and aquatic habitat. In both areas, the largest observable changes occurred in areas that were located in close proximity downstream from high to moderate severity burned areas. While we did not monitor turbidity quantitatively, visual observations indicated that turbidity was very high during both visits at all site locations, relative to other nearby streams that were unaffected by the fire.

4.2 Dollar Ridge

In-stream habitat conditions substantially changed between our two site visits in the reaches located above the pinnacles (proximate to the burned area); however, below the pinnacles, there is little qualitative change in habitat conditions. DR1 is the most upstream site and is located along a large, historic debris flow fan. During visit 1 the river was a single channel above and below the fan This fan acts as a barrier to river meandering by pinning the channel against the opposite valley wall (Fig. 4-3). The channel is considerably deeper and narrower with swift moving currents. During visit 2, we observed a fresh deposit of sediment on top of the historic fan. The new addition of material changed the morphology of the river both upstream and downstream of the fan. A large, submerged gravel bar had formed at the downstream portion of the site. The channel consisted of multiple channels above the fan, choked by the fan back into a single-channel for the length of the fan and then spanned out into a braided network below the fan (Fig. 4-4). Downstream of the fan deposit, there was significant aggradation of the channel and banks due to the deposition of fine materials. The channel remained braided for 500m downstream from the DR1 fan until it converges back into a single threaded channel. The channel then alternated between a single- and multi-channel network for two kilometers downstream, where site DR2 is located.

During visit 1 at DR2, the channel was a multi-threaded system and the main portion of the channel flowed beside the road. The channel consisted primarily of riffles with slower moving side channels. There was no evidence of large-scale sediment delivery prior to the fire. During visit 2, we observed a moderate debris flow, which occurred at the adjacent upstream drainage, located between sites DR1 and DR2. The

Fig. 4-3. Aerial view of DR1 and the historic fan with fresh sediment deposit. The arrow indicates direction of flow.

addition of ash, mud and sand caused DR2 to be unrecognizable and the main channel was abandoned because the upstream portion had aggraded with fine sediment (Fig. 4-5, Fig. 4-6). The river flowed through an intricate, multi-channel network of slower moving water. Burned trees located in the valley bottom caught debris flowing through, creating small barriers composed of mostly fallen branches. The water was forced to divert around these small barriers, creating a unique and complex habitat (Fig. 4-7). The downstream end of DR2 appeared to be returning to a single threaded channel. The threads began to converge towards the lower end of the reach into what was the main channel prior to the fire.

Fig. 4-4. Aerial view of DR1 and the historic fan showing the multi-threaded channel portions above and below the fan. The red arrow points to the historic fan. The white arrow indicates flow direction.

There were no observable changes between visits 1 and 2 at DR3, DR4 and DR5. There were no significant differences in fines or larger grains present, nor were there apparent changes in general morphology, presence of bars, or bank failure.

4.3 Trail Mountain

The Trail Mountain fire resulted in a high proportion of the area burning at high severity. However, the area received little precipitation post-fire, and thus the qualitative changes to the stream channels were minimal. Rilling, gullying and sheetwash delivered fine sediment to upper site locations (TM1-3). Most sediment input consisted of sand, ash, and mud.

Visit 1

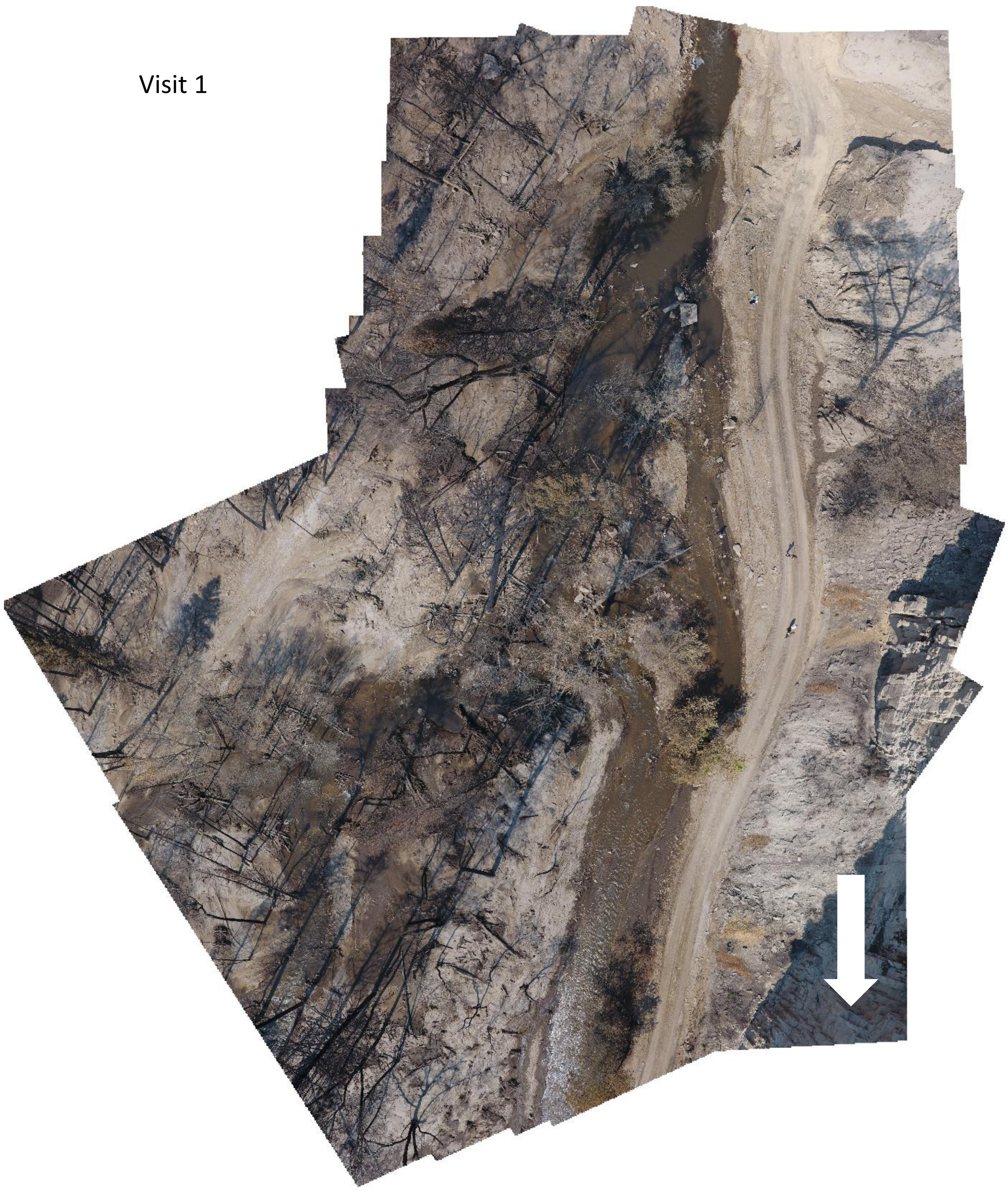

Fig. 4-5. Aerial view of DR2. The photo from visit 1 shows the main channel filled with water and the photo from visit 2 shows the abandoned channel. Water is returning to the downstream portion. Channel flow is indicated by the white arrow.

Visit 2

Fig. 4-5. (cont.)

Fig. 4-6. Aerial view of DR2 during visit 2. The pre-fire main channel (indicated by the red arrow) is abandoned and water has diverted to the right in a multi-threaded system. Flow direction is indicated by the white arrow.

TM1 is the most-upstream site surrounded by steep hillslopes with thick, unburned vegetation. However, directly upstream is a large area of high severity burn. TM1 increased in fines; however, no other qualitative geomorphic changes, such as development of fans or bars, occurred.

The area upstream from site TM2 burned at moderate to high severity with steep hillslopes, similar to TM1. Some vegetation persisted near the banks at the top portion of the site, but all trees on the hillslopes were moderately to severely burned. During visit 1, there was no evidence of hillslope sediment transport into the channel. However, during visit 2, we observed a small deposit of fine sediment, consisting of sand, mud and black

Fig. 4-7. Trees along the valley bottom of DR2 catch debris and create water diversion and a multi-threaded system. Flow direction is indicated by the white arrow.

ash that spilled into the channel and covered the left side of the bank at the downstream end of the site (Fig. 4-8). This deposit seemed to be the result of rilling/gullying and significantly increased the presence of fines at TM2.

TM3 is located at the mouth of a steep drainage and burned at moderate to high severity. All vegetation was at minimum moderately burned on both sides of the hillslopes. This site is surrounded by steep hillslopes and significantly increased in the proportion of fines (Fig. 4-9). Ash covered the hillslopes and entered the river from both sides of the canyon. During visit 1, there was no evidence of hillslope sediment transport into the channel. During visit 2, there was no one clear source of the addition of fines,

Fig. 4-8. Black ash and fines that entered the river at TM2 observed during and visit 2. Flow direction is indicated by the white arrow.

and it seems that fines were transported from both hillslopes via sheet wash or rilling or transported from upstream.

The most downstream sites, located above (TM4) and below (TM5) Crandall Canyon mine, remained qualitatively unchanged between visits. No noticeable geomorphic changes occurred at either site. Additionally, there was no substantial change in vegetation.

4.4 Sample and assessment of gravel size distributions

Both Dollar Ridge and Trail Mountain sites significantly increased in the proportion of fines between site visits 1 and 2. We performed the K-S statistical test to

Fig. 4-9. Steep hillslopes covered in ash input fines into the system at TM3. Flow direction is indicated by the white arrow.

test for significant changes in grain size distribution using three metrics: the grain size, grain embeddedness, and percent of grain surrounded by fines (Table 4-3).

Table 4-3
Dollar Ridge and Trail Mountain K-S test results with associated significance ($p < 0.1$ (*); $p < 0.01$ (**); $p < 0.001$ (***)). The associated D-values are in each K-S box.

	Dollar Ridge			Trail Mountain		
Site	Grain size (mm)	Embeddedness (%)	Fines (%)	Grain size (mm)	Embeddedness (%)	Fines (%)
1	0.4***	0.4***	0.4***	0.2*	0.3***	0.3***
2	0.4***	0.9***	0.9***	0.2	0.1	0.2*
3	0.2*	0.2	0.3***	0.4***	0.3***	0.3***
4	0.2**	0.3***	0.1	0.1	0.1	0.2*
5	0.1	0.2	0.2**	0.1	0.2**	0.3***

The grain size distribution changed at all Dollar Ridge sites on the Strawberry River; however, those changes were not spatially uniform (Table 4-3, Fig. 4-10). For example, DR1 and DR2 showed a significant increase in fines by all three metrics. DR3 and DR4, directly downstream from DR1 and DR2, significantly increased in proportion of smaller framework grains; however, there was not a statistically significant fining effect in all three metrics. DR5, located on the Red Creek tributary and approximately 4 km away from a high severity burn area, did not show significant changes in grain size distribution, but slightly increased in fines surrounding grains, indicating less pore space in the matrix. All site locations decreased in the largest grain size class.

TM1, located directly below a large high severity burn area, and TM3, located at the mouth of a drainage dominated by moderate to high severity burned areas, increased in the proportion of fines according to all three metrics, resulting in a greater proportion of smaller framework grains and decreased pore space within the matrix (Fig. 4-11). TM2, TM4 and TM5 did not significantly change in grain size distribution; however, significant increases in percent fines surrounding the grain indicate decreased pore space within the matrix.

4.*5 Determine if spawning females can move gravel*

Using the 10% guideline, the upper limit of moveable grain size of Brown Trout is approximately 25 mm. Most sites did not change in the proportion of moveable grains, except TM1 and TM2, which increased (Table 4-2). The 10% guideline Brown Trout RF model performs well at classifying the change in movable gravel, correctly classifying changes in the proportion of moveable gravel with approximately 100% accuracy ($K > 0.9$, $p < 0.001$). The RF model suggests that the most important variables controlling the

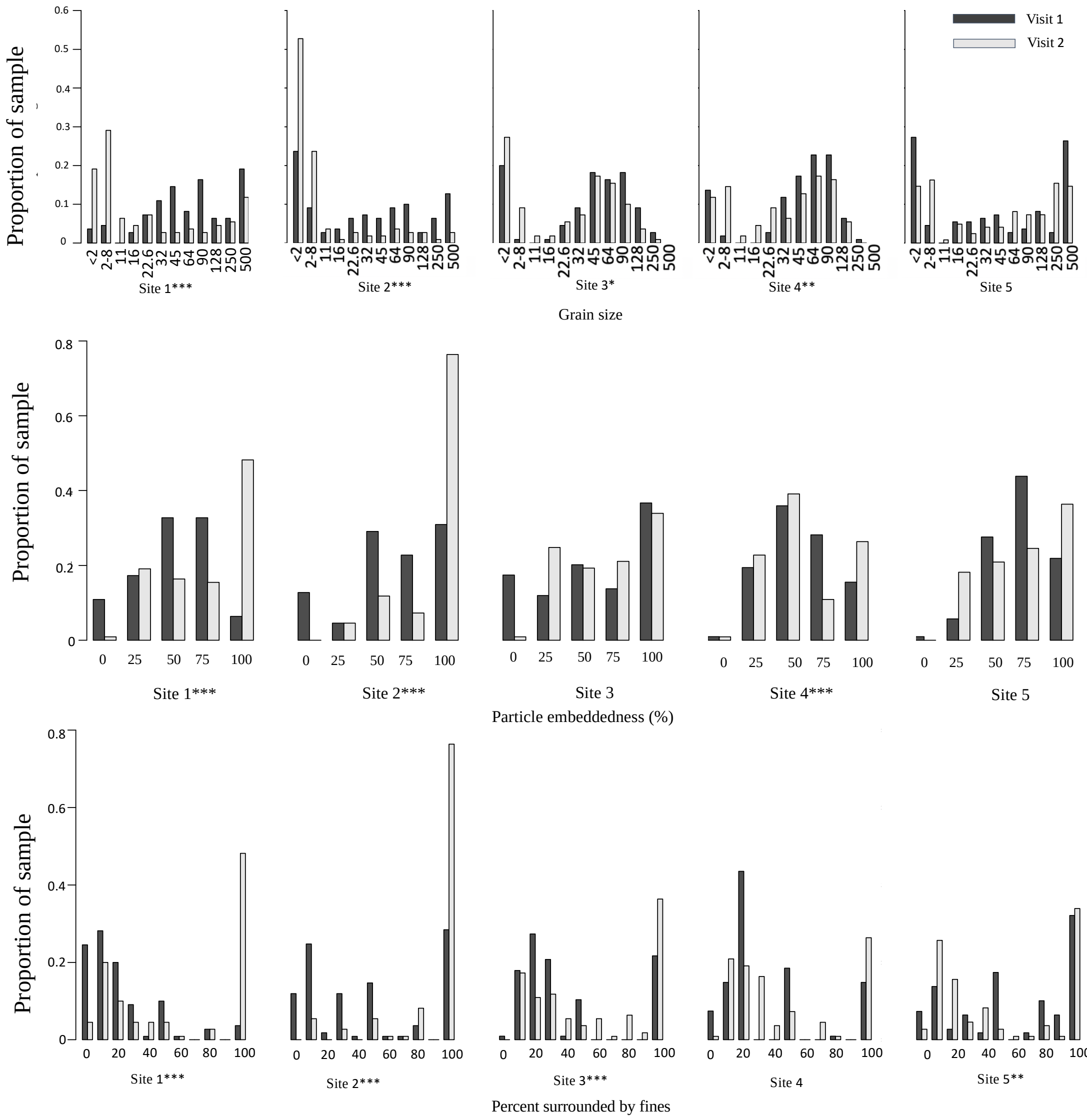

Fig. 4-10. Grain size distribution changes for all three metrics at each Dollar Ridge site. Significance levels of the K-S test results are shown adjacent to the site number ($p < 0.1$ (*); $p < 0.01$ (**); $p < 0.001$ (***)).

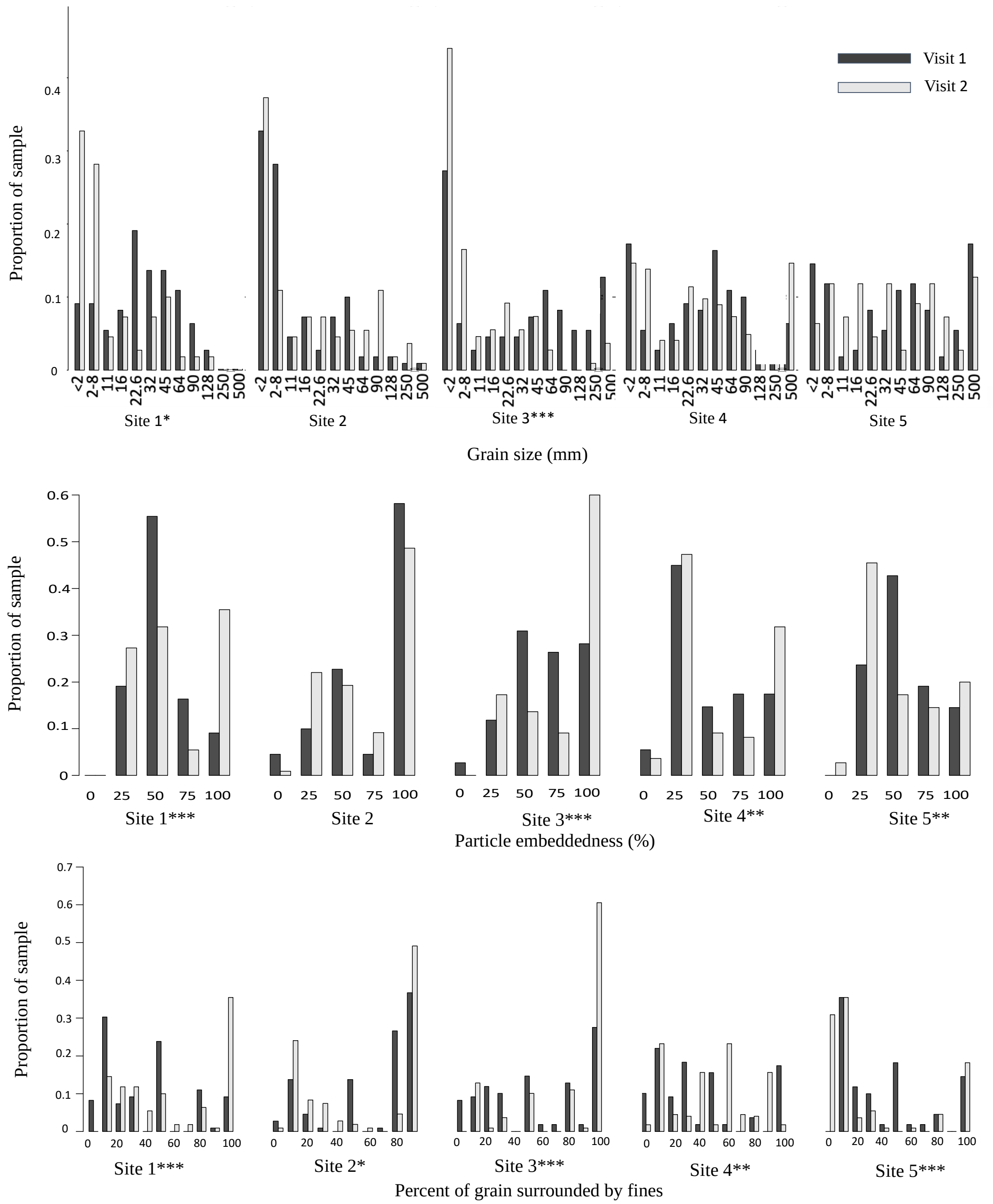

Fig. 4-11. Grain size distribution changes for each metric at each Trail Mountain site location. Significance levels of the K-S test results are shown adjacent to the site number ($p < 0.1$ (*); $p < 0.01$ (**); $p < 0.001$ (***)).

change in the proportion of movable grains are percentage of upstream area that burned at high to moderate severity and pre-fire D_{50} (Fig. 4-12).

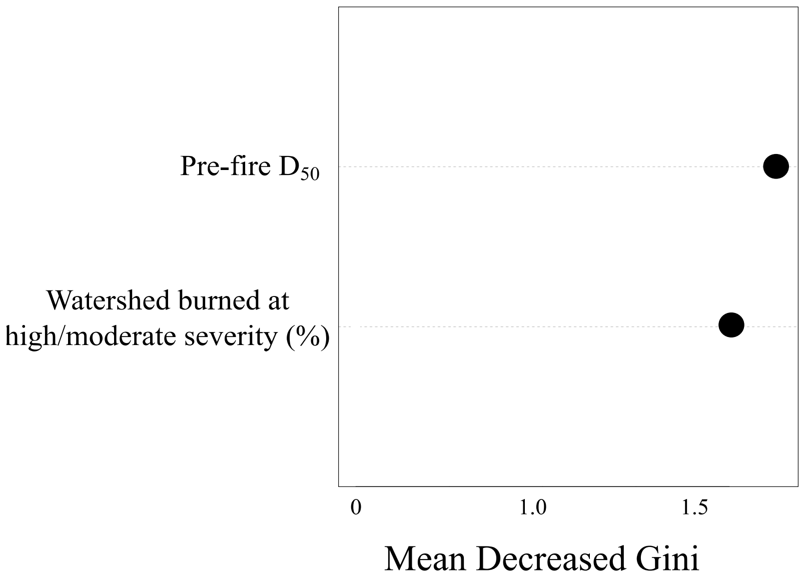

Fig. 4-12. The variable importance plot for the result of the 10% guideline for Brown Trout RF model shows that low severity burn area (%) and distance from high/moderate severity burn areas are the most important variables in the RF model. A higher mean decrease Gini value indicates higher variable importance.

Partial dependence plots show the predicted relationship between the change in the proportion of movable grain size and the two significant predictor variables (Fig. 4-13). Positive values indicate that the classification being analyzed is more likely for that corresponding value of the independent variable (https://cran.r-project.org/web/packages/randomForest/). Negative values indicate that the classification is less likely for that corresponding value of the independent variable. Zero indicates that the RF model cannot predict classification for that value. Thus, greater amounts of area burned at high to moderate severity are correlated with no change in proportion of moveable grain size and lesser amounts of area burned at high to moderate severity are

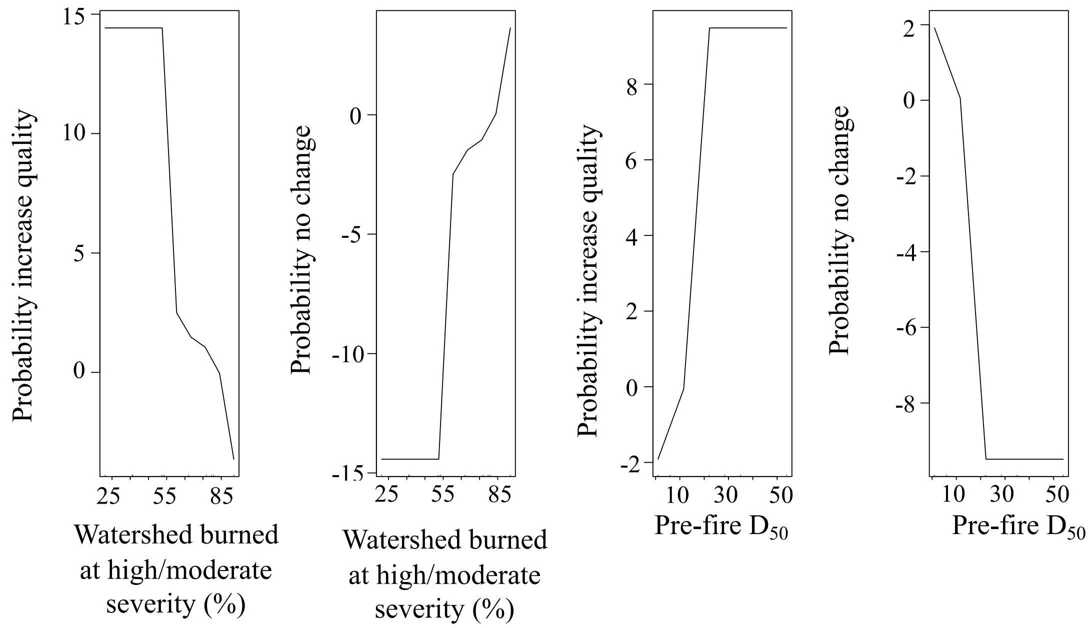

Fig. 4-13. Partial dependence plots for each important variable indicated by the 10% guideline RF model for Brown Trout.

correlated with an increased proportion of movable grains. Additionally, smaller pre-fire river bed D_{50} values (grains less than 20 mm) are correlated with no change in habitat. Pre-fire D_{50} values greater than 20 mm are correlated with increases in the proportion of movable grains.

Using the 10% guideline, the upper limit of movable grain size for Cutthroat Trout was approximately 20 mm and the proportion of movable grains did not change at most site locations. TM3 was the only location where the ability to move grains changed, and in that case, it increased (Table 4-2). The RF model was not able to identify important predictor variables to explain the observed variance in changes according to the 10% guideline for Cutthroat Trout ($K < 0.59$).

Our second metric used to determine the upper limit of movable grain size, F_m, provided different results than the 10 % guideline. Although Brown and Cutthroat Trout have slightly different body lengths, the upper limit of movable grains for both species was approximately equal to 70 mm. Therefore, we only ran one random forest model that incorporated the F_m metric for both species. The F_m metric indicated opposite trends for each of the fires regarding the proportion of movable grains (Table 4-2). All Dollar Ridge sites increased in the proportion of movable gravel, except for DR5, which decreased. All Trail Mountain sites decreased in proportion of moveable grains, except for TM3, which increased. The RF model is unable to identify important predictor variables and there is a high degree of randomness within the model ($K < 0.59$).

4.6 Determine spatial availability to build redds

N_{redds} is a function of F_m, and thus the results of N_{redds} are identical to those of F_m. TM3 and DR1-4 increased in spatial availability of areas suitable for redd habitat, while all other sites decreased in spatial availability. The RF model failed to identify significant predictor variables ($K < 0.59$).

4.7 Determine if incubation is affected

Working under the assumption that incubation is negatively impacted when fines (< 2 mm) exceed 14% of the grain size distribution, we found that incubation was largely unaffected across all sites. Only one site (TM 5) decreased from above to below the 14% threshold, indicating habitat improvement, and one site (DR1) increased from below to above the 14% threshold, indicating habitat degradation (Table 4-2). The RF model was not able to parse out important predictor variables to predict changes in the proportion of fines (K < 0.59).

4.8 Determine if emergence if affected

Working under the assumption that increasing the proportion of grain sizes between 2 and 11 mm will inhibit successful emergence, we found that emergence was negatively affected at most sites (Table 4-2). However, TM2 decreased in grain sizes between 2 to 11 mm, indicating an improvement for successful emergence. The emergence RF model did not identify important predictor variables with high explanatory power as there was a high degree of randomness within the model (K < 0.59).

4.9 Changes in optimal grain size proportion

Analysis of the proportion of optimal grain sizes metric produces varying results, indicating no change at several sites and decreased habitat quality at the remainder of sites. Specifically, sites TM2, TM3, DR3, and DR4 did not significantly change in the proportion of optimal grain sizes. All other sites decreased in optimal grain size proportions. The RF model was not able to indicate important variables, and the final model contains a high degree of randomness (K < 0.59).

5. Discussion

Large landscape changes occurred in steep, burned areas that received precipitation. Riverbed grain size proportions shifted to larger proportions of smaller grains as new sediment was introduced into the river system. The fine sediment added into the river affected the quality of salmonid habitat at all three lift stages. Most of these effects decreased habitat quality, however, this is highly dependent on the habitat quality metric and mode of analysis.

Both F_m and the 10% guideline are two commonly used methods to estimate the upper limits of gravel mobility of spawning female fish. However, in our application results between the methods differed considerably. Even though both methods use body length to calculate the upper limit of moveable grain size, they produced inconsistent upper limits which may contribute to contradicting conclusions as to changes in habitat quality. The F_m and 10% guideline only matched at one site for Cutthroat Trout (TM3) and did not match at any sites for Brown Trout. The difference could represent uncertainty and poor constraints on the upper limit of grain sizes that fish are able to mobilize. Additionally, these methods only characterize habitat quality for one phase of the life cycle and, therefore, are an incomplete representation of overall habitat quality, or overall changes in habitat quality.

The contradicting results obtained with the Fm and the 10% guideline compared with the optimal grain size proportion analysis may be due to the failure of both Fm and the 10% guideline to account for increases in grains less than 11 mm, which are known to hinder incubation and emergence and, therefore, may over estimate benefits of changes in bed material. The optimal grain size proportion metric indicated a decrease in fish habitat by accounting for bed material that affects the ability to dig redds, incubation and successful emergence. Accounting for grains less than 11mm, the change in optimal grain size proportion may be a more accurate way to determine habitat change compared to F_m and the 10% guideline.

The ability of Brown Trout to move grains using the 10% guideline was the only RF model that provided significant results, indicating that upstream area burned at high to moderate severity and pre-fire D_{50} were important predictor variables. Wildfires of high and moderate severity significantly impact changes in vegetation and runoff which contribute to increased sediment transport (Moody et al., 2013; Moody and Martin, 2001). The correlation between greater amounts of high to moderate severity burn areas and increased sediment input into river networks, and subsequent changes in river bed grain size, is supported throughout previous literature (Burton, 2005; Isaak et al., 2009; Sestrich et al., 2011). Our study indicates that greater percentages of high to moderate severity burn areas correlate with no change in the grain size distribution. However, this may be due to the fact that our higher severity burn area (Trail Mountain sites) received less precipitation than the lower severity sites. It is expected that when Trail Mountain receives more precipitation, sediment will be delivered to the channel and the grain size distribution will change. When the pre-fire streambed condition is characterized as coarse, i.e., $D_{50} > 20$ mm, large sediment pulses contribute fine grains, thereby increasing the proportion of movable grains. Although most of our sites did not increase in habitat quality, other studies have shown that mass sediment transport can improve habitat quality (Copp, 1989; Everest and Meehan, 1981; Reeves et al., 1995). In order to better understand how sediment pulses alter the different habitat quality metrics, future work should examine how fire characteristics and the input of sediment after wildfire act to benefit or degrade habitats in rivers with different pre-fire D_{50} values.

It was surprising that valley confinement and slope were not identified as significant variables driving changes in bed grain size, as these metrics are commonly used in sediment transport to determine erosional and depositional events (Czuba et al., 2017; Thompson and Croke, 2013). Failure of the RF model to identify these variables may result from the limited number of observations (n = 10) and the homogeneity within this dataset caused by both fires being located in catchments with steep hillslopes and semi-confined and confined streams. More work needs to be done to develop a more reliable and comprehensive approach to evaluate where sediment will degrade or enhance trout habitat along the river network.

All techniques in this study used traditional pebble counts, which have limitations that may affect the assessment of habitat quality. First, pebble counts measure grains along their b-axis, and do not account for total mass of the grain. This may significantly affect results as grains classified as equal may have different masses and shapes that hinder movability. Second, pebble counts do not account for fining below the surface. Although we attempt to incorporate measurements of matrix grains, fines do not increase linearly with depth in the sediment column and this effect cannot be captured with traditional pebble counts. This effect is especially important when salmonids dig redds, thereby coming into contact with a different proportion of fines than is present on the riverbed surface and thus that habitat may not be suitable for incubation or emergence. If managers do not account for this effect, they might misclassify the habitat quality and risk wasting resources trying to establish fish habitat in an unsuitable location. Future studies should examine how the proportion of subsurface fines influence salmonid's ability to successfully incubate and emerge.

Where species are at risk, restoration efforts may be necessary to ensure viable fish habitat. Restoration managers should consider long-term consequences of sediment transport caused by fire. Land managers should be aware of significant fining of the bed material after wildfires and the associated risks for fish communities. Development of metrics that accurately classify changes in salmonid habitat quality at multiple life stages over time will allow managers to improve restoration plans, such as reintroduction of salmonids to disturbed areas. To refine predictions of habitat quality change, more work is needed to understand how fire affects the upper limit of grain mobility and the proportion of fine grain-sizes < 11 mm. Increasing our understanding in these areas will allow for more effective implementation of restoration projects in fire-affected river networks.

6. Conclusion

Salmonid habitats in mountain streams within the western US are at increasing risk from wildfire and the subsequent flooding, erosion and sediment transport. The results of this study bring to light two significant findings. First, determining the upper limit of grain size mobility is highly dependent on the method used and current methods may over predict benefits to habitat quality by not accounting for the effects of increased fines on incubation and emergence. A better understanding of the impacts of the proportions of grains, both less than 10 mm and below the upper limit of grain sizes that fish are able to mobilize, on the different salmonid life stages is needed to develop improved habitat quality models. Second, fire causes significant habitat changes along river networks. Increases in overland flow and changes in sediment transport mechanism introduce significant amounts of sediment into rivers, both acting to improve habitat by replenishing spawning gravel and degrade habitat with the addition of large proportions of fine grains. These affects are not uniform along the river network and their effect on habitat quality changes over time.

Although changes in habitat quality are not yet predictable, fire specific characteristics, such as burn severity, clearly impact changes in riverbed grain size distributions and subsequent habitat. In order to determine how fires affect fish habitat, we first need a method to accurately quantify optimal fish habitat. Future work analyzing more sites and a longer time frame would enhance understanding of variables that impact fish habitat quality, such as slope and confinement. Development of these tools is needed for land managers as they continue to face climate driven changes, and require a better interdisciplinary understanding of abiotic and biotic interactions.

References

Benda, L., Miller, D., Bigelow, P., Andras, K., 2003. Effects of post-wildfire erosion on channel environments, Boise River, Idaho. For. Ecol. Manage. 178, 105–119. https://doi.org/10.1016/S0378-1127(03)00056-2

Birchell, G.J., Boren, N., Hedrick, T., Utah Division of Wildlife, V., 2014. Fish Populations In the Strawberry River , Utah : A Present Assessment with Historical Comparison Fish Populations In the Strawberry River , Utah : A Present Assessment with Historical Comparison. Salt Lake City, UT.

Bjornn, T.C., 1969. Embryo survival and emergence studies. Idaho Fish and Same Department, Federal Aid in Fish Restoration, Project F-49-R7, Job 5, Job Completion Report.

Brieley, G., Fryirs, K.A., 2005. Geomorphology and River Management: Applications of the River Styles Framework. Blackwell Publishing, Oxford.

Brown, D.K., Echelle, A. a, Propst, D.L., Brooks, J.E., Fisher, W.L., 2001. Catastrophic wildfire and number of populations as factors influencing risk of extinction for Gila trout (Oncorhynchus gilae). West. North Am. Nat.

Burton, T.A., 2005. Fish and stream habitat risks from uncharacteristic wildfire: Observations from 17 years of fire-related disturbances on the Boise National Forest, Idaho. For. Ecol. Manage. 211, 140–149. https://doi.org/10.1016/j.foreco.2005.02.063

Cannon, S.H., 2001. Debris-flow generation from recently burned watersheds. Environ. Eng. Geosci. 7, 321–341.

Cederholm, C.J., Salo, E.O., 1979. The Effects of Logging Road Landslide Siltation on the Salmon and Trout Spawning Gravels of Stequaleho Creek and the Clearwater River Basin, Jefferson County, Washington, 1972-1978 x–99.

CHaMP. (Columbia Habitat Monitoring Program), 2016. Scientific Protocol for Salmonid Habitat Surveys within the Columbia Habitat Monitoring Program. Prep. by CHaMP Bonnev. Power Adm. 145.

Cohen, J., 1960. A Coefficient of Agreement for nomail scales. Educ. Psychol. Meas. 20, 37–46.

Copp, G.H., 1989. The habitat diversity and fish reproductive function of floodplain ecosystems. Environ. Biol. Fishes 26, 1–27. https://doi.org/10.1007/BF00002472

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Kyle, T., Gibson, J., Lawler, J.J., Beard, H., Hess, T., 2007. Random Forests for Classification in Ecology Published by : Ecological Society of America. Ecology 88, 2783–2792.

Czuba, J.A., Foufoula-Georgiou, E., Gran, K.B., Belmont, P., Wilcock, P.R., 2017. Interplay between spatially explicit sediment sourcing, hierarchical river-network structure, and in-channel bed material sediment transport and storage dynamics. J. Geophys. Res. Earth Surf. 122, 1090–1120. https://doi.org/10.1002/2016JF003965

Everest, F.H., Meehan, W.R., 1981. Some effects of debris torrents on habitat of anadromous salmonids, in: In: National Council for Air and Stream Improvement, Inc., Measuring and Assessing the Effectiveness of Alternative Forest Management Practices on Water Quality. NCASI Technical Bulletin 353. Research Triangle Park, North Carolina,. pp. 23–30.

Franssen, J., Lapointe, M., Magnan, P., 2014. Geomorphic controls on fine sediment reinfiltration into salmonid spawning gravels and the implications for spawning habitat rehabilitation. Geomorphology 211, 11–21. https://doi.org/10.1016/j.geomorph.2013.12.019

Fryirs, K.A., Wheaton, J.M., Brierley, G.J., 2016. An approach for measuring confinement and assessing the influence of valley setting on river forms and processes. Earth Surf. Process. Landforms 41, 701–710. https://doi.org/10.1002/esp.3893

Greig, S.M., Sear, D.A., Carling, P.A., 2007. A review of factors influencing the availability of dissolved oxygen to incubating salmonid embryos. Hydrol. Process. 21, 323–334. https://doi.org/10.1002/hyp

Gresswell, R.E., 1999. Fire and Aquatic Ecosystems in Forested Biomes of North America. Trans. Am. Fish. Soc. https://doi.org/10.1577/1548-

8659(1999)128<0193:FAAEIF>2.0.CO;2

Harshbarger, T.J., Porter, P.., 1982. Embryo Survival and Fry Emergence from Two Methods of Planting Brown Trout Eggs. North Am. J. Fish. Manag. 2, 84–89.

Hawke, S.P., 1978. Stranded redds of quinnat salmon in the Mathias River, South Island New Zealand. New Zeal. J. Mar. Freshw. Res. 12, 167–171.

Isaak, D., Luce, C., Rieman, B., Nagel, D., Peterson, E., Horan, D., Parkes, S., Chandler, G., 2009. Effects of Climate Change and Recent Wildfires on Stream Temperature and Thermal Habitat for Two Salmonids in a Mountain River Network. Ecol. Appl. 20, 100319061507001. https://doi.org/10.1890/09-0822

Kondolf, G.M., 2000. Assessing Salmonid Spawning Gravel Quality. Trans. Am. Fish. Soc. 129, 262–281. https://doi.org/10.1109/LCOMM.2018.2864265

Larsen, I.J., MacDonald, L.H., Brown, E., Rough, D., Welsh, M.J., Pietraszek, J.H., Libohova, Z., de Dios Benavides-Solorio, J., Schaffrath, K., 2009. Causes of Post-Fire Runoff and Erosion: Water Repellency, Cover, or Soil Sealing? Soil Sci. Soc. Am. J. 73, 1393. https://doi.org/10.2136/sssaj2007.0432

McHugh, M.L., 2012. Interrater reliability: the kappa stastic. Biochem Med 22, 276–282.

McNeil, W.J., Ahnell, W.H., 1964. Success of pink salmon spawning relative to size of spawning bed materials. U.S> fish and Wildlife Service, Special Scientific Report-Fisheries.

Moody, J.A., Martin, D.A., 2001. Initial hydrologic and geomorphic response following a wildfire in the Colorado front range. Earth Surf. Process. Landforms 26, 1049–1070. https://doi.org/10.1002/esp.253

Moody, J.A., Shakesby, R.A., Robichaud, P.R., Cannon, S.H., Martin, D.A., 2013. Current research issues related to post-wildfire runoff and erosion processes. Earth-Science Rev. 122, 10–37. https://doi.org/10.1016/j.earscirev.2013.03.004

Olson, J.R., Hawkins, C.P., 2012. Predicting natural base-flow stream water chemistry in the western United States. Water Resour. Res. 48, 1–19. https://doi.org/10.1029/2011WR011088

Overstreet, B.T., Riebe, C.S., Wooster, J.K., Sklar, L.S., Bellugi, D., 2016. Tools for gauging the capacity of salmon spawning substrates. Earth Surf. Process. Landforms 41, 130–142. https://doi.org/10.1002/esp.3831

Phillips, R.W., Lantz, R.L., Clarie, E.W., Morning, J.R., 1975. Some effects of gravel mixtures on emergence of coho salmon and steelhead trout fry. Trans. Am. Fish. Soc. 104, 461–466.

Propst, D.L., Stefferud, J.A., 1997. Population dynamics of Gila trout in the Gila River drainage of the south-western United States. J. Fish Biol. https://doi.org/10.1006/jfbi.1997.0512

Prudencio, L., Choi, R., Esplin, E., Ge, M., Gillard, N., Haight, J., Belmont, P., Flint, C., 2018. The Impacts of Wildfire Characteristics and Employment on the Adaptive Management Strategies in the Intermountain West. Fire 1, 46. https://doi.org/10.3390/fire1030046

Reeves, G.H., Benda, L.E., Burnett, K.M., Bisson, P. a, Sedell, J.R., 1995. A disturbance-based ecosystem approach to maintaining and restoring freshwater habitats of evolutionarily significant units of anadromous salmonids in the Pacific Northwest. Am. Fish. Soc. Symp. 17, 334–349. https://doi.org/10.1.1.218.5159

Riebe, C.S., Sklar, L.S., Overstreet, B.T., Wooster, J.K., 2014. Optimal reproduction in salmon spawning substrates linked to grain size and fish length. Water Resour. Res. 50, 898–918. https://doi.org/10.1002/2013WR014231

Roghair, C.N., Dolloff, C.A., Underwood, M.K., 2002. Response of a Brook Trout Population and Instream Habitat to a Catastrophic Flood and Debris Flow. Trans. Am. Fish. Soc. 131, 718–730. https://doi.org/10.1577/1548-8659(2002)131<0718:ROABTP>2.0.CO;2

Sedell, E.R., Gresswell, R.E., Mcmahon, T.E., 2015. Predicting spatial distribution of post fi re debris fl ows and potential consequences for native trout in headwater streams. Freshw. Sci. 34, 1558–1570. https://doi.org/10.1086/684094.

Service, US Forest, 2018. UT645 Soils Manuscript.

Sestrich, C.M., McMahon, T.E., Young, M.K., 2011. Influence of fire on native and nonnative salmonid populations and habitat in a western Montana basin. Trans. Am. Fish. Soc. 140, 136–146. https://doi.org/10.1080/00028487.2011.557019

Shepard, B.B., May, B.E., Urie, W., 2005. Status and Conservation of Westslope Cutthroat Trout within the Western United States. North Am. J. Fish. Manag. 25, 1426–1440. https://doi.org/10.1577/M05-004.1

Staley, D.M., Negri, J.A., Kean, J.W., Laber, J.L., Tillery, A.C., Youberg, A.M., 2017. Prediction of spatially explicit rainfall intensity–duration thresholds for post-fire debris-flow generation in the western United States. Geomorphology 278, 149–162. https://doi.org/10.1016/j.geomorph.2016.10.019

Strobl, C., Malley, J., Tutz, G., 2009. An Introduction to Recursive Partitioning: Rationale, Application, and Characteristics of Classification and Regression Trees, Bagging, and Random Forests. Psychol. Methods 14, 323–348.

https://doi.org/10.1037/a0016973

Tagart, J.V., 1984. Coho salmon survival from egg deposition to fry emergence., in: Olympic Wild Fish Conference, Port Angeles, Washington. pp. 173–181.

Tappel, P.D., Bjornn, T.C., 2004. A New Method of Relating Size of Spawning Gravel to Salmonid Embryo Survival. North Am. J. Fish. Manag. 3, 123–135. https://doi.org/10.1577/1548-8659(1983)3<123:anmors>2.0.co;2

Team, I.B.A., 1998. SUM FISH POP STRAW RIVER, Utah.

Thompson, C., Croke, J., 2013. Geomorphic effects, flood power, and channel competence of a catastrophic flood in confined and unconfined reaches of the upper Lockyer valley, southeast Queensland, Australia. Geomorphology 197, 156–169. https://doi.org/10.1016/j.geomorph.2013.05.006

US Forest Service, 2019. Vegetation Classification, Mapping and Quantitative Inventory.

Wagenbrenner, J.W., Robichaud, P.R., 2014. Post-fire bedload sediment delivery across spatial scales in the interior western United States. Earth Surf. Process. Landforms 39, 865–876. https://doi.org/10.1002/esp.3488

Wenger, S.J., Isaak, D.J., Luce, C.H., Neville, H.M., Fausch, K.D., Dunham, J.B., Dauwalter, D.C., Young, M.K., Elsner, M.M., Rieman, B.E., Hamlet, A.F., Williams, J.E., 2011. Flow regime, temperature, and biotic interactions drive differential declines of trout species under climate change. Proc. Natl. Acad. Sci. 108, 14175–14180. https://doi.org/10.1073/pnas.1103097108

Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase Western U.S. forest wildfire activity. Science (80-.). 313, 940–943. https://doi.org/10.1126/science.1128834

Williams, J.E., Haak, A.L., Neville, H.M., Colyer, W.T., 2009. Potential Consequences of Climate Change to Persistence of Cutthroat Trout Populations. North Am. J. Fish. Manag. 29, 533–548. https://doi.org/10.1577/m08-072.1

Woods, S.W., Balfour, V.N., 2008. The effect of ash on runoff and erosion after a severe forest wildfire, Montana, USA. Int. J. Wildl. Fire 17, 535–548. https://doi.org/10.1071/WF07

CHAPTER 5

CONCLUSION

This thesis explores the links between wildfire and its impacts on both human communities and aquatic habitat conditions. Our findings suggest that there are both positive and negative benefits to all communities, human and aquatic, after fire. It also identifies areas where further research should be focused in order to better understand how different environmental conditions influence post-wildfire dynamics.

Our research indicates three main findings involving fire and management strategies within the Intermountain West. First, there are heterogenous increases in fire frequency and burn trends at regional, state and county scales. We found that, in the Intermountain West, there were more frequent and larger rural fires, and more frequent urban fires, over the 32 year study period. Second, there are positive economic impacts immediately after fire, which weaken over time. This result is consistent with previous literature (Nielsen-Pincus et al., 2013; Schoennagel et al., 2004). Our study focused on employment data to analyze economic impacts, but a boarder analysis of additional economic sectors would enhance our ability to understand economic impacts in a more comprehensive manner. Third, our research indicated that most managers recognize the changing fire trends and effects on economies and are implementing adaptive management strategies to reduce negative impacts. However, managers face considerable challenges in adapting, such as budget limitations and bureaucratic inefficiencies. These challenges make it unlikely that new policies will be immediately adopted. Recognizing and understanding those challenges and limitations is imperative to identifying alternative strategies that may be easier to implement or improve processes for implementation.

Human communities are not the only ones affected by fire, as wildfire significantly changes hydrologic and geomorphic processes affecting salmonid communities. As discussed in Chapter 3, our analyses indicated that fire severity and local geologic watershed characteristics are the most important variables influencing the magnitude of change in runoff after a wildfire. Our results align with past literature, which indicates that fire severity greatly impacts landscape response to fire (Moody et al., 2013; Moody and Martin, 2001). Runoff increased up to 880 percent, and over 100 percent in many cases. Our study indicates that areas can increase as short-lived or persistent changes in runoff after wildfire, either of which may have important implications for ecological processes. Therefore, we find that changes in runoff cannot be measured using a single metric, as doing so may lead to an underestimation of impacts. Managers should be aware of this when planning assessment and restoration efforts, as underpredicting changes in key flow metrics could lead to wasted efforts and resources. Including more fires in future studies may bring to light additional important environmental variables with higher explanatory power.

Increased runoff ultimately leads to changes in erosion and sediment transport, thus altering the riverbed grain size distribution. Salmonids depend on grain size distributions that are primarily composed of gravel small enough to move, so they can dig redds, but large enough not to hinder incubation or emergence success (Kondolf, 2000). Chapter 4 showed that fire severity and geologic watershed characteristics significantly alter salmonid habitat by changing riverbed grain size distributions, though changes are not uniform along the river network and will change over time. Consistent with past literature, both positive and negative effects on habitat quality occur, but the magnitude and implications of the changes depend on the metric of interest (e.g., incubation success, emergence success, proportion of movable grains) and the methods used for assessment (Brown et al., 2001; Gresswell, 1999; Sedell et al., 2015). Managers should be especially aware of how both upper and lower limits of grain size affect habitat quality and account for changes in both. Broadening this study to include more fires and a longer time scale may help to better understand environmental variables that impact changes in riverbed grain size distributions.

The combined results of this work have important fire science and management implications. Results from chapter 2, indicating general trends of increasing fire frequency and burn area within the Intermountain West and subsequent impacts on rural and urban economies and the perceptions of those economic impacts on managers and policy decision makers, are reasonably applicable to other communities affected by fire. Results from chapter 3-4, providing insight to increases in runoff and changes in riverbed grain size in relation to salmonid habitat, may be applicable in additional mid- to high-elevation forested areas, but they should be tested further to better understand fire-landscape interactions. Understanding how specific communities may change, both positively and negatively, from fire is imperative as wildfires continue to increase and affect more communities and will provide information necessary to implement efficient and effective fire management in order to protect community health and minimize risk within the western US.

References

Brown, D.K., Echelle, A. a, Propst, D.L., Brooks, J.E., Fisher, W.L., 2001. Catastrophic wildfire and number of populations as factors influencing risk of extinction for Gila trout (Oncorhynchus gilae). West. North Am. Nat.

Dunn, C.J., Calkin, D.E., Thompson, M.P., 2017. Towards enhanced risk management: planning, decision making and monitoring of US wildfire response. Int. J. Wildl. Fire 26, 551–556. https://doi.org/10.1071/WF17089

Gresswell, R.E., 1999. Fire and Aquatic Ecosystems in Forested Biomes of North America. Trans. Am. Fish. Soc. https://doi.org/10.1577/1548-8659(1999)128<0193:FAAEIF>2.0.CO;2

Kondolf, G.M., 2000. Assessing Salmonid Spawning Gravel Quality. Trans. Am. Fish. Soc. 129, 262–281. https://doi.org/10.1109/LCOMM.2018.2864265

Moody, J.A., Martin, D.A., 2001. Initial hydrologic and geomorphic response following a wildfire in the Colorado front range. Earth Surf. Process. Landforms 26, 1049–1070. https://doi.org/10.1002/esp.253

Moody, J.A., Shakesby, R.A., Robichaud, P.R., Cannon, S.H., Martin, D.A., 2013. Current research issues related to post-wildfire runoff and erosion processes. Earth-Science Rev. 122, 10–37. https://doi.org/10.1016/j.earscirev.2013.03.004

Nielsen-Pincus, M., Moseley, C., Gebert, K., 2013. The effects of large wildfires on employment and wage growth and volatility in the western United States. J. For. 111, 404–411. https://doi.org/http://dx.doi.org/10.5849/jof.13-012

Schoennagel, T., Veblen T. T., Romme, W. H., 2004. The Interaction of Fire, Fuels, and Climate across Rocky Mountain Forests. Bioscience 54, 661. https://doi.org/10.1641/0006-3568(2004)054[0661:TIOFFA]2.0.CO;2

Sedell, E.R., Gresswell, R.E., Mcmahon, T.E., 2015. Predicting spatial distribution of post fi re debris fl ows and potential consequences for native trout in headwater streams. Freshw. Sci. 34, 1558–1570. https://doi.org/10.1086/684094.

Wine, M.L., Makhnin, O., Cadol, D., 2018. Nonlinear Long-Term Large Watershed Hydrologic Response to Wildfire and Climatic Dynamics Locally Increases Water Yields. Earth’s Futur. 6, 997–1006. https://doi.org/10.1029/2018EF000930

APPENDICES

Appendix A- Chapter 2 Supplemental Material

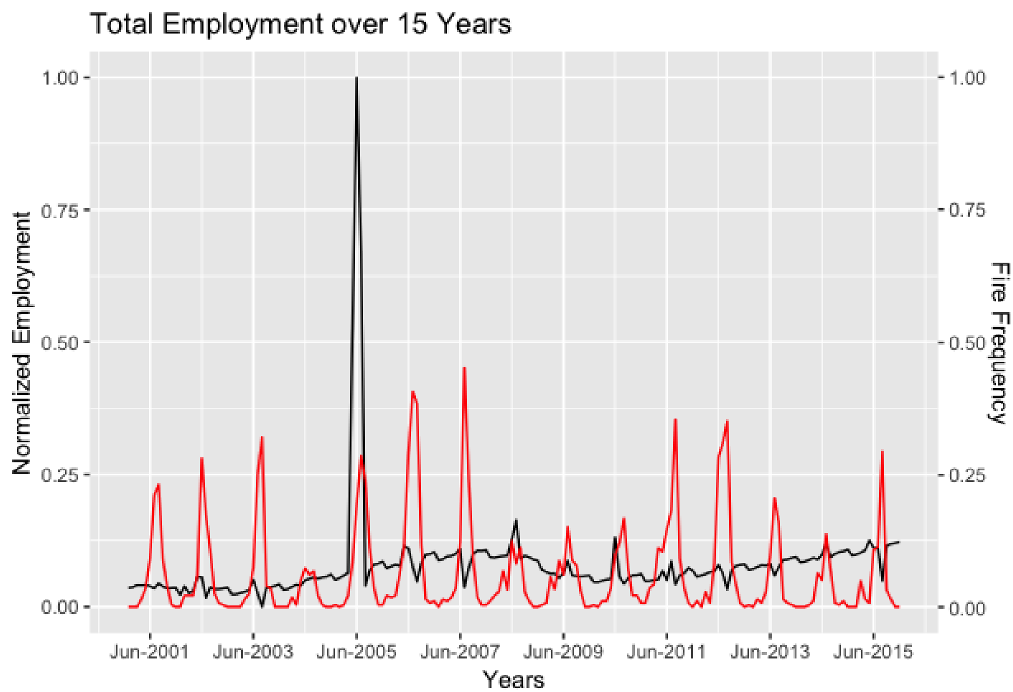

Figure S1. Normalized total employment and fire frequency for the IMW from 2001-2015.

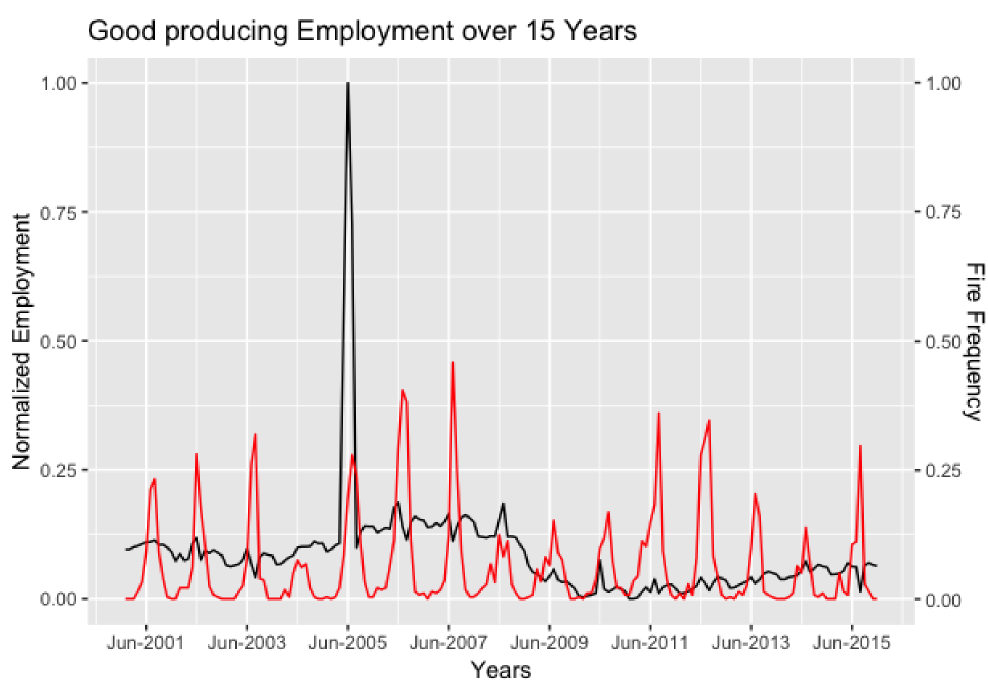

Figure S2. Normalized Goods-Producing employment and fire frequency for the IMW from 2001-2015.

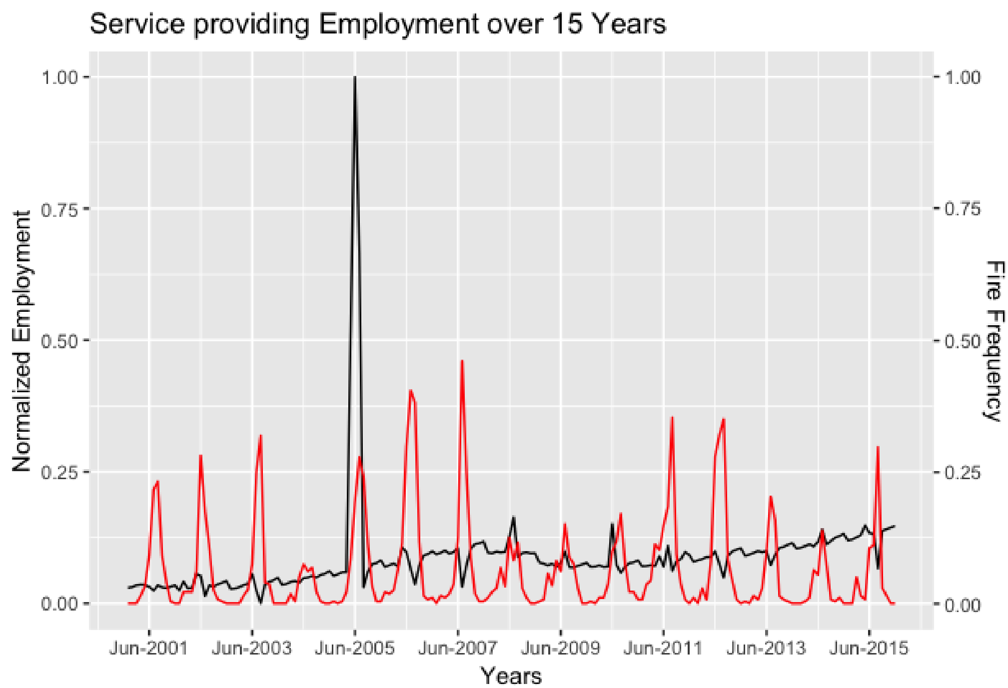

Figure S3. Normalized Service-Providing employment and fire frequency for the IMW from 2001-2015.

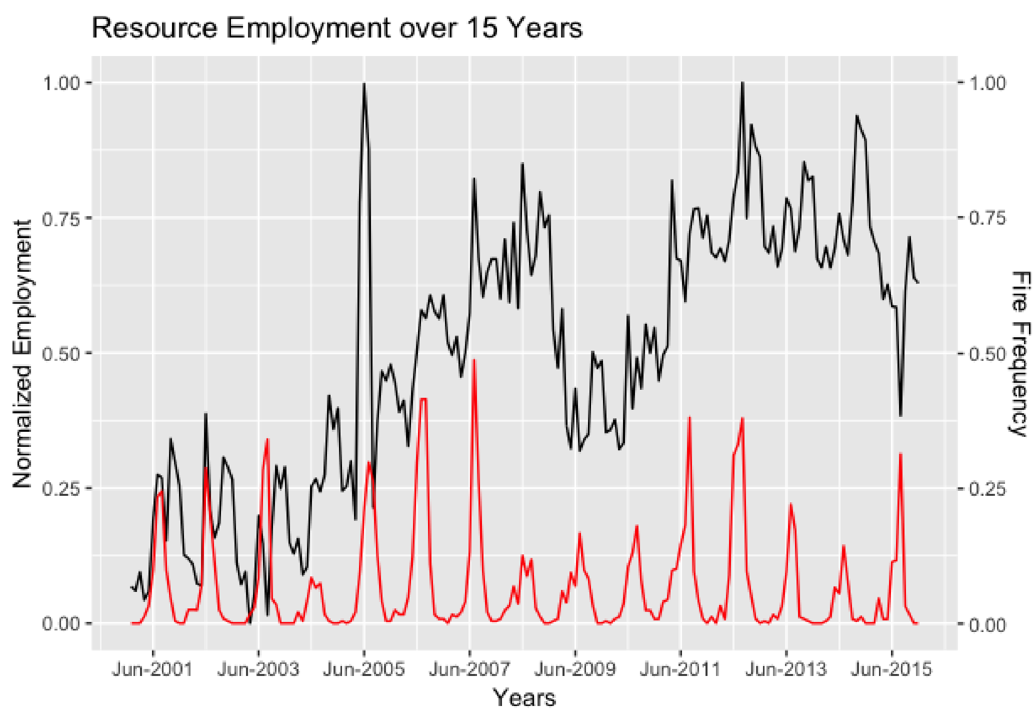

Figure S4. Normalized Natural Resource and Mining employment and fire frequency for the IMW from 2001-2015.

Figure S5. Normalized Leisure and Hospitality employment and fire frequency for the IMW from 2001-2015.

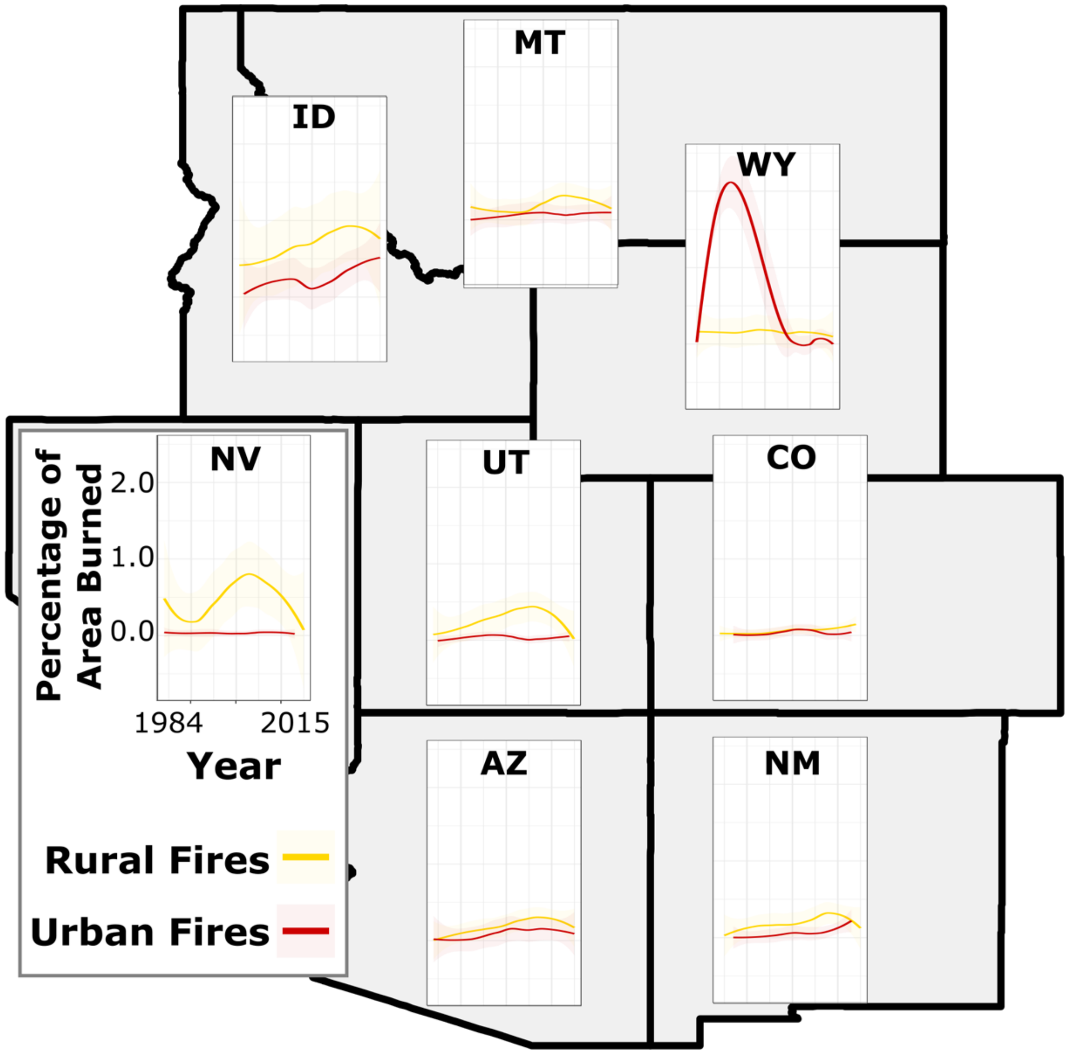

Figure S6. State-level LOESS curves in percentage of area burned for rural and urban fires.

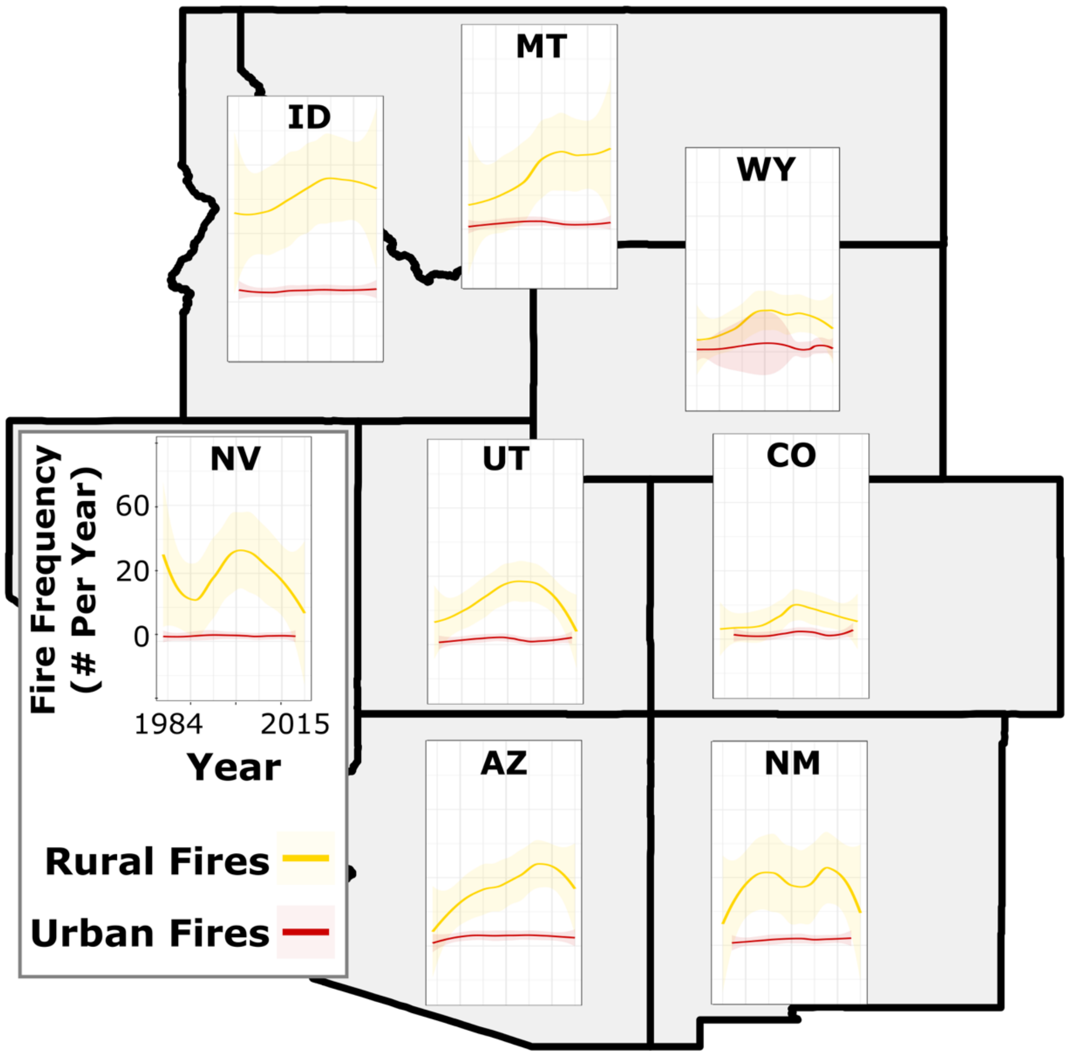

Figure S7. State-level LOESS curves in the fire frequency for rural and urban fires.

Table S1. Regression results for (I) Total Employment for the 12-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). The first column presents the results for All Fires within all 281 IMW counties (44,666 observations), the second column represents the results for Rural Fires (44,360 observations), the third column represents the results for Urban Fires (41,429 observations), and the last column represents the results for the 14 Increasing Focal Counties (2,274 observations). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable			
	Effects of Fires on Employment (%)			
	All Fires	Rural Fires	Urban Fires	Increasing Focal Counties
Fire Happened	0.005*	0.005	-0.001	0.020***
	(0.003)	(0.003)	(0.008)	(0.007)
1 Months After	0.005**	0.006**	-0.006	0.010
	(0.003)	(0.003)	(0.007)	(0.006)
2 Months After	0.005**	0.005*	-0.001	0.010
	(0.003)	(0.003)	(0.007)	(0.006)
3 Months After	0.004	0.004	0.0003	0.002
	(0.003)	(0.003)	(0.007)	(0.006)
4 Months After	0.005*	0.004	0.002	0.002
	(0.003)	(0.003)	(0.007)	(0.007)
5 Months After	0.002	0.002	0.005	-0.005
	(0.003)	(0.003)	(0.007)	(0.007)
6 Months After	0.001	0.001	0.006	0.0002
	(0.003)	(0.003)	(0.007)	(0.006)
7 Months After	0.001	0.001	0.003	-0.0003
	(0.003)	(0.003)	(0.007)	(0.007)
8 Months After	0.003	0.003	0.006	0.0001
	(0.003)	(0.003)	(0.007)	(0.007)
9 Months After	0.002	0.002	0.003	0.005
	(0.003)	(0.003)	(0.007)	(0.007)
10 Months After	0.002	0.003	0.0004	-0.002
	(0.003)	(0.003)	(0.007)	(0.007)
11 Months After	0.001	0.003	-0.005	-0.003
	(0.003)	(0.003)	(0.007)	(0.007)

Table SI. (cont.)

12 Months After	0.003	0.004	-0.004	0.008
	(0.003)	(0.003)	(0.007)	(0.007)
Observations	44,666	44,360	41,429	2,274
R^2	0.996	0.996	0.996	0.996
Adjusted R^2	0.996	0.996	0.996	0.996
Residual Std. Error	0.115	0.115	0.116	0.100
	[df=44,333]	[df=44,027]	[df=41,097]	[df=2,208]

Table S2. Regression results of the (1) Goods Producing sector for the 12-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable			
	Effects of Fires on Employment (%)			
	All Fires	Rural Fires	Urban Fires	Increasing Focal Counties
Fire Happened	0.007	0.009	0.003	0.032***
	(0.006)	(0.006)	(0.015)	(0.012)
1 Months After	0.010**	0.011**	-0.00004	0.010
	(0.005)	(0.005)	(0.014)	(0.010)
2 Months After	0.007	0.008	0.002	0.013
	(0.005)	(0.005)	(0.014)	(0.011)
3 Months After	0.004	0.005	0.004	0.012
	(0.005)	(0.005)	(0.014)	(0.011)
4 Months After	0.007	0.008	0.008	0.015
	(0.005)	(0.005)	(0.014)	(0.011)
5 Months After	0.005	0.006	0.009	0.003
	(0.005)	(0.005)	(0.014)	(0.011)
6 Months After	0.005	0.005	0.005	-0.0002
	(0.005)	(0.005)	(0.014)	(0.011)
7 Months After	0.002	0.003	-0.004	-0.003
	(0.005)	(0.005)	(0.014)	(0.011)
8 Months After	0.005	0.005	0.006	-0.008
	(0.005)	(0.006)	(0.014)	(0.011)

Table S2. (cont.)

9 Months After	0.004	0.005	0.003	0.011
	(0.005)	(0.006)	(0.014)	(0.011)
10 Months After	0.007	0.007	0.007	0.013
	(0.005)	(0.006)	(0.014)	(0.011)
11 Months After	0.007	0.008	0.005	0.008
	(0.005)	(0.006)	(0.014)	(0.011)
12 Months After	0.009*	0.010*	0.004	0.018*
	(0.005)	(0.006)	(0.014)	(0.011)
Observations	44,165	43,877	40,966	2,209
R^2	0.984	0.984	0.984	0.977
Adjusted R^2	0.984	0.984	0.984	0.977
Residual Std. Error	0.222	0.223	0.224	0.166
	[df=43,832]	[df=43,544]	[df=40,635]	[df=2,143]

Table S3. Regression results of the (2) Service Providing sector for the 12-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable			
	Effects of Fires on Employment (%)			
	All Fires	Rural Fires	Urban Fires	Increasing Focal Counties
Fire Happened	0.002	0.003	-0.004	-0.002
	(0.003)	(0.003)	(0.008)	(0.007)
1 Months After	0.004*	0.005*	-0.009	0.008
	(0.003)	(0.003)	(0.007)	(0.006)
2 Months After	0.004	0.005	-0.006	0.003
	(0.003)	(0.003)	(0.007)	(0.006)
3 Months After	0.002	0.004	-0.004	-0.002
	(0.003)	(0.003)	(0.007)	(0.006)
4 Months After	0.002	0.002	-0.002	0.00003
	(0.003)	(0.003)	(0.007)	(0.006)
5 Months After	-0.0004	-0.0002	0.001	-0.008
	(0.003)	(0.003)	(0.007)	(0.006)

Table S3. (cont.)

6 Months After	-0.001	-0.002	0.003	-0.003
	(0.003)	(0.003)	(0.007)	(0.006)
7 Months After	0.001	0.001	0.003	0.0002
	(0.003)	(0.003)	(0.008)	(0.006)
8 Months After	0.002	0.001	0.003	-0.001
	(0.003)	(0.003)	(0.008)	(0.006)
9 Months After	0.003	0.002	0.003	0.002
	(0.003)	(0.003)	(0.008)	(0.006)
10 Months After	0.0002	0.001	-0.001	-0.005
	(0.003)	(0.003)	(0.008)	(0.006)
11 Months After	0.0002	0.001	-0.007	-0.006
	(0.003)	(0.003)	(0.008)	(0.006)
12 Months After	0.001	0.001	-0.007	-0.004
	(0.003)	(0.003)	(0.008)	(0.006)
Observations	44,177	43,873	40,955	2,248
R^2	0.996	0.996	0.996	0.997
Adjusted R^2	0.996	0.996	0.996	0.997
Residual Std. Error	0.116	0.115	0.117	0.095
	[df=43,844]	[df=43,540]	[df=40,623]	[df=2,182]

Table S4. Regression results of the (1a) Good Producing: Natural Resource and Mining sector for the 12-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable			
	Effects of Fires on Employment (%)			
	All Fires	Rural Fires	Urban Fires	Increasing Focal Counties
Fire Happened	0.006	0.004	-0.006	0.072***
	(0.008)	(0.008)	(0.021)	(0.019)
1 Months After	-0.002	0.001	-0.011	-0.007
	(0.007)	(0.007)	(0.020)	(0.016)
2 Months After	-0.001	-0.0004	-0.011	0.012
	(0.007)	(0.008)	(0.020)	(0.016)

Table S4. (cont.)

3 Months After	-0.003	-0.004	-0.015	0.003
	(0.007)	(0.008)	(0.020)	(0.017)
4 Months After	0.004	0.003	-0.024	0.014
	(0.007)	(0.008)	(0.020)	(0.017)
5 Months After	0.002	0.002	-0.022	0.006
	(0.007)	(0.008)	(0.020)	(0.017)
6 Months After	-0.001	0.002	-0.023	-0.018
	(0.007)	(0.008)	(0.020)	(0.017)
7 Months After	-0.009	-0.007	-0.032	-0.026
	(0.007)	(0.008)	(0.020)	(0.017)
8 Months After	-0.003	-0.003	-0.021	-0.011
	(0.007)	(0.008)	(0.020)	(0.017)
9 Months After	-0.004	-0.007	-0.022	0.006
	(0.007)	(0.008)	(0.020)	(0.017)
10 Months After	0.001	-0.003	-0.014	0.020
	(0.008)	(0.008)	(0.020)	(0.017)
11 Months After	0.001	0.002	-0.007	0.003
	(0.008)	(0.008)	(0.020)	(0.017)
12 Months After	0.007	0.007	-0.009	0.046***
	(0.008)	(0.008)	(0.020)	(0.017)
Observations	39,406	39,112	36,346	2,181
R^2	0.953	0.954	0.953	0.950
Adjusted R^2	0.952	0.953	0.953	0.948
Residual Std. Error	0.306	0.304	0.305	0.252
	[df=39,082]	[df=38,788]	[df=36,023]	[df=2,116]

Table S5. Regression results of the (2a) Service Providing: Leisure and Hospitality sector for the 12-month window post-fire for years 2001-2015 (*p<0.1; **p<0.05; ***p<0.01). Effects of fires on employment are presented in percentages. The standard error for each regression is presented in parentheses.

	Dependent variable			
	Effects of Fires on Employment (%)			
	All Fires	Rural Fires	Urban Fires	Increasing Focal Counties
Fire Happened	0.00002	0.001	-0.013	-0.015
	(0.005)	(0.005)	(0.013)	(0.010)
1 Months After	0.005	0.005	-0.031**	0.009
	(0.004)	(0.004)	(0.012)	(0.008)
2 Months After	0.006	0.008	-0.017	-0.005
	(0.005)	(0.005)	(0.012)	(0.009)
3 Months After	0.003	0.003	-0.010	-0.001
	(0.005)	(0.005)	(0.012)	(0.009)
4 Months After	0.001	0.0003	-0.010	-0.006
	(0.005)	(0.005)	(0.012)	(0.009)
5 Months After	0.0001	-0.001	0.0003	-0.015*
	(0.005)	(0.005)	(0.012)	(0.009)
6 Months After	0.0001	-0.0004	0.012	-0.003
	(0.005)	(0.005)	(0.012)	(0.009)
7 Months After	0.001	0.001	0.013	-0.003
	(0.005)	(0.005)	(0.013)	(0.009)
8 Months After	0.0001	-0.001	0.002	-0.001
	(0.005)	(0.005)	(0.013)	(0.009)
9 Months After	0.0001	-0.0002	0.003	-0.0005
	(0.005)	(0.005)	(0.013)	(0.009)
10 Months After	-0.006	-0.006	-0.014	-0.005
	(0.005)	(0.005)	(0.013)	(0.009)
11 Months After	-0.006	-0.006	-0.024*	-0.010
	(0.005)	(0.005)	(0.013)	(0.009)
12 Months After	-0.002	-0.002	-0.022*	-0.006
	(0.005)	(0.005)	(0.013)	(0.009)

Table S5. (cont.)

Observations	43,967	43,699	40,772	2,242
R^2	0.989	0.989	0.989	0.994
Adjusted R^2	0.989	0.989	0.988	0.994
Residual Std. Error	0.195	0.194	0.195	0.136
	[df=43,635]	[df=43,367]	[df=40,441]	[df=2,176]

Appendix B- Chapter 3 Supplemental Material

Link to data files:
https://usu.app.box.com/folder/24421232493

List of variables used in Random Forest Analysis (* indicates calculated using MTBS burn severity data):

1. *Percent upstream area burned at high severity
2. *Percent upstream area burned at high or moderate severity
3. *Percent upstream area burned at moderate severity
4. *Percent upstream area burned at low
5. *Percent upstream area burned at very low/unburned severity
6. *Total percent of upstream watershed burned
7. Soil erodibility factor
8. Average wetland index
9. Base flow index of watershed
10. Mean rate of biological nitrogen fixation from the cultivation of crops in watershed
11. Percent clay
12. Rock composition strength
13. Mean elevation
14. Hydrologic conductivity
15. Average K factor
16. Predicted mean winter temperature of 2014
17. Mean percent of lithologic sodium oxide content in surface or near surface geology within catchment
18. Annual gradient map of precipitation-weighted mean deposition for ammonium ion concentration wet deposition for 2008
19. Annual gradient map of precipitation-weighted mean deposition for nitrate ion concentration wet deposition for 2008
20. Mean percent lithological nitrogen content in surface or near surface geology
21. Mean organic matter content (percent by weight) of soils
22. Mean percent of lithological phosphorous content in surface or near surface geology
23. Percent of catchment area classified as ag land cover occurring on slopes greater than or equal to 20 percent
24. Percent of catchment area classified as ag land cover occurring on slopes greater than or equal to 10 percent
25. Percent of watershed classified as barren land cover
26. Percent forest classified as evergreen forest land cover 2006
27. Percent forest classified as evergreen forest land cover 2011
28. Percent forest classified as deciduous forest land cover 2011
29. Percent forest classified as grassland land cover 2011
30. Percent forest classified as hay land use 2011

31. Percent of watershed area classified as shrub/scrub land cover 2011
32. Percent of watershed area classified as woody wetland land cover 2011
33. Percent imperviousness of anthropogenic surfaces
34. Percent forest classified as mixed deciduous/evergreen forest land cover 2011
35. Percent nonagricultural nonnative introduced or managed vegetation landcover type
36. Percent of watershed area classified as lithology type: non-carbon residual
37. Percent of watershed area classified as lithology type: alkaline intrusive volcanic rock
38. Percent of watershed area classified as lithology type: silcic residual material
39. Percent of watershed area classified as lithology type: extrusive volcanic rock
40. Percent of watershed area classified as lithology type: alkaline intrusive volcanic rock
41. Percent of watershed area classified as lithology type: colluvial sediment
42. Percent of watershed area classified as lithology type: glacial till, clayey
43. Percent of watershed area classified as lithology type: glacial till, loamy
44. Percent of watershed area classified as lithology type: glacial till, course-textured
45. Percent of watershed area classified as lithology type: glacial outwash and glacial lake sediment, course-textured
46. Percent of watershed area classified as lithology type: glacial lake sediment, fine-textured
47. Percent of watershed area classified as lithology type: hydric, peat, and muck
48. Percent of watershed area classified as lithology type: eolian sediment, course-textured (sand dunes)
49. Percent of watershed area classified as lithology type: eolian sediment, fine-textured (glacial loess)
50. Percent of watershed area classified as lithology type: alluvium and fine-textured coastal zone sediment
51. Percent of watershed area classified as lithology type: alluvium and course-textured coastal zone sediment
52. Percent of watershed classified as lithology type: water
53. Mean permeability of soils
54. Mean pesticide use
55. PRISM climate data- 30-year normal minimum temperature
56. Mean bedrock depth
57. Mean annual runoff
58. Percent sand content of soils
59. Mean percent of lithologic silicon dioxide content in surface or near surface geology within watershed
60. Annual gradient map of precipitation-weighted mean deposition for inorganic nitrogen wet deposition from nitrate and ammonium for 2008
61. Mean percent of lithological sulfur content in surface or near surface geology
62. PRISM climate data- 30-year normal minimum temperature
63. PRISM climate data- 30-year normal maximum temperature
64. Average water table depth
65. Watershed area

Appendix C- Chapter 4 Supplemental Material

Link to data files:
https://usu.app.box.com/folder/24421232493

List of variables used in Random Forest Analysis (*indicates calculated using MTBS burn severity data):

1. *Percent upstream area burned at high severity
2. *Percent upstream area burned at high or moderate severity
3. *Percent upstream area burned at moderate severity
4. *Percent upstream area burned at low
5. *Percent upstream area burned at very low/unburned severity
6. *Total percent of upstream watershed burned
7. Soil erodibility factor
8. Valley Confinement
9. D_{50} at the time of visit 1
10. Average wetland index
11. Base flow index of watershed
12. Mean rate of biological nitrogen fixation from the cultivation of crops in watershed
13. Percent clay
14. Rock composition strength
15. Mean elevation
16. Hydrologic conductivity
17. Average K factor
18. Predicted mean winter temperature of 2014
19. Mean percent of lithologic sodium oxide content in surface or near surface geology within catchment
20. Annual gradient map of precipitation-weighted mean deposition for ammonium ion concentration wet deposition for 2008
21. Annual gradient map of precipitation-weighted mean deposition for nitrate ion concentration wet deposition for 2008
22. Mean percent lithological nitrogen content in surface or near surface geology
23. Mean organic matter content (percent by weight) of soils
24. Mean percent of lithological phosphorous content in surface or near surface geology
25. Percent of catchment area classified as ag land cover occurring on slopes greater than or equal to 20 percent
26. Percent of catchment area classified as ag land cover occurring on slopes greater than or equal to 10 percent
27. Percent of watershed classified as barren land cover
28. Percent forest classified as evergreen forest land cover 2006
29. Percent forest classified as evergreen forest land cover 2011
30. Percent forest classified as deciduous forest land cover 2011

31. Percent forest classified as grassland land cover 2011
32. Percent forest classified as hay land use 2011
33. Percent of watershed area classified as shrub/scrub land cover 2011
34. Percent of watershed area classified as woody wetland land cover 2011
35. Percent imperviousness of anthropogenic surfaces
36. Percent forest classified as mixed deciduous/evergreen forest land cover 2011
37. Percent nonagricultural nonnative introduced or managed vegetation landcover type
38. Percent of watershed area classified as lithology type: non-carbon residual
39. Percent of watershed area classified as lithology type: alkaline intrusive volcanic rock
40. Percent of watershed area classified as lithology type: silcic residual material
41. Percent of watershed area classified as lithology type: extrusive volcanic rock
42. Percent of watershed area classified as lithology type: alkaline intrusive volcanic rock
43. Percent of watershed area classified as lithology type: colluvial sediment
44. Percent of watershed area classified as lithology type: glacial till, clayey
45. Percent of watershed area classified as lithology type: glacial till, loamy
46. Percent of watershed area classified as lithology type: glacial till, course-textured
47. Percent of watershed area classified as lithology type: glacial outwash and glacial lake sediment, course-textured
48. Percent of watershed area classified as lithology type: glacial lake sediment, fine-textured
49. Percent of watershed area classified as lithology type: hydric, peat, and muck
50. Percent of watershed area classified as lithology type: eolian sediment, course-textured (sand dunes)
51. Percent of watershed area classified as lithology type: eolian sediment, fine-textured (glacial loess)
52. Percent of watershed area classified as lithology type: alluvium and fine-textured coastal zone sediment
53. Percent of watershed area classified as lithology type: alluvium and course-textured coastal zone sediment
54. Percent of watershed classified as lithology type: water
55. Mean permeability of soils
56. Mean pesticide use
57. PRISM climate data- 30-year normal minimum temperature
58. Mean bedrock depth
59. Mean annual runoff
60. Percent sand content of soils
61. Mean percent of lithologic silicon dioxide content in surface or near surface geology within watershed
62. Annual gradient map of precipitation-weighted mean deposition for inorganic nitrogen wet deposition from nitrate and ammonium for 2008
63. Mean percent of lithological sulfur content in surface or near surface geology
64. PRISM climate data- 30-year normal minimum temperature
65. PRISM climate data- 30-year normal maximum temperature

66. Average water table depth
67. Watershed area

Appendix D- Permission to Reprint: Fire

June 3, 2019

Dear Courtney;

I am in the process of preparing my thesis in the Watershed Science department at Utah State University. I hope to complete my degree program in August.

I am requesting your permission to include the attached material as shown. I will include acknowledgments and/or appropriate citations to your work as shown and copyright and reprint rights information in a special appendix. The bibliographic citation will appear at the end of the manuscript as shown. Please advise me of any changes you require.

Please indicate your approval of this request by signing in the space provided, attaching any other form or instruction necessary to confirm permission. If you have any questions, please call me at the number below.

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(Prudencio et al., 2018); Prudencio, L., Choi, R., Esplin, E., Ge, M., Gillard, N., Haight, J., Belmont, P., and Flint, C., 2018, The Impacts of Wildfire Characteristics and Employment on the Adaptive Management Strategies in the Intermountain West: Fire, v. 1, p. 46, doi: 10.3390/fire1030046.

Signed: ______________________________

June 3, 2019

Dear Jeff:

I am in the process of preparing my thesis in the Watershed Science department at Utah State University. I hope to complete my degree program in August.

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Please indicate your approval of this request by signing in the space provided, attaching any other form or instruction necessary to confirm permission. If you have any questions, please call me at the number below.

I hope you will be able to reply immediately.

Thank you for you cooperation,

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